Experiments on the Role of the Number of Alternatives in Choice

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Abstract

Whereas people are typically thought to be better off with more choices, large sets may lead to "choice paralysis". This thesis explores the processes underlying the choice from multiple alternatives in different settings. First, we propose that satisfaction is an inverted U-shaped function of the number of alternatives. This proposition is derived theoretically by considering the benefits and costs of different numbers of alternatives, and validated in several behavioral experiments. Second, we investigate the computational processes used to make choices from multiple alternatives under extreme time pressure using an eye-tracking technique. We find that choices are well-described by a sequential search model, in which people randomly fixate on items, measure their values, and choose the best item seen. Third, we study the neural bases of choice from multiple alternatives using fMRI. The results demonstrate that brain activity is modulated by the number of choice items and by the subjective choice experience of people.

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To all my teachers, friends and family I dedicate this thesis.

Introduction

Let no one say that taking action is hard.
Action is aided by courage, by the moment, by impulse,
and the hardest thing in the world is making a decision

Franz Grillparzer (1791-1872),
Austrian author

In today's world, people face a great numbers of choice alternatives involving both small and large stakes, e.g., from chocolates and cereals to health plans and pension schemes. The every-day decisions in a typical supermarket involve choosing a yogurt out of 150 types of yogurts or a bottle of wine out of 3600 sorts of wines. Yet, although both classic economics and psychology emphasize the benefits of more choice (see, e.g., Langer & Rodin, 1976; Zuckerman et al., 1978; Ryan & Deci, 2000), having many alternatives can lead to choice paralysis and less satisfaction with decisions (Schwartz, 2000; 2004; Iyengar & Lepper, 2000; Iyengar, Wells, & Schwartz, 2006). So how much choice is enough?

This thesis explores how people make choices from sets with multiple alternatives and investigates the mechanisms underlying the choice overload phenomenon. There are several gaps in the previous research that this thesis aims to fill. First, previous literature focused mostly on studying choices from limited (up to 5 options) and extensive (25-30 options) numbers of alternatives. Very few sources include choice sets with an intermediate number of options. We emphasize that it is also important to predict human behavior and satisfaction when one faces intermediate sets. This thesis studies choices from small, intermediate and extensive sets of alternatives. We explore how satisfaction and actual behavior changes as a *function* of the number of items in the set.

Second, previous research focused mostly on outcomes of choice behavior (e.g., the number of choices made, quality of decisions, etc.). Little attention was paid to understanding the processes underlying choice from multiple alternatives. This occurs mainly because there are few tools which can be used for uncovering such processes. In this thesis we aim to explore the processes driving choice behavior from multiple alternatives. To shed light on mechanisms underlying choice behavior, we use various experimental methods including eye-tracking and functional magnetic resonance imaging (fMRI) techniques. The use of both behavioral and biological data provide a powerful tool for exploring and understanding the actual processes that individuals use to make choice decisions.

In the first chapter we provide and test an explicit theoretical rationale for how satisfaction from choice varies as a function of set size. We propose that satisfaction from choice is an inverted U-shaped function of the number of alternatives. We derive this proposition theoretically by considering the benefits and costs of different numbers of alternatives. We suggest that both benefits and costs increase with the number of alternatives, but while the former increase and "satiate" the latter increase and "escalate". We assume that satisfaction is defined as net benefits (i.e., benefits less costs), and therefore, is an inverted U-shaped function of a set size. We further provide experimental verification of our proposition. Moreover, hypothesizing differences in cognitive costs, we demonstrate how these affect the relative location of the function's peak. We conduct eye-tracking and questionnaire studies to verify our conjecture about cognitive costs. We demonstrate effects of psychic costs by showing that satisfaction is diminished if people are made aware of the existence of other choice sets. Furthermore, effects due to gender further demonstrate the role of individual differences.

In the second chapter we study the computational processes people use to make real choices among familiar snack foods under extreme time pressure and option overload. Surprisingly, given the speed of the process and the fact that subjects only fixate on a subset of the items, we find that average choice efficiencies in all choice sets are large (about 80%). This suggests that subjects are able to make good decisions in every day conditions (e.g., at a supermarket aisle) even under severe time pressure. To explore why this is the case we use the eye-tracking data to characterize in detail the computational process used to make the decisions. We find that choices are well-described by a sequential search model in which subjects randomly fixate on items in order to measure their values as long as they have time and then choose the best item that they have seen. Although the process works well in many circumstances, we also find that it exhibits significant display-driven biases that can be potentially exploited by sellers to manipulate choice.

The third chapter aims to investigate the neural bases of choice overload phenomena. In our fMRI experiment, subjects faced different-sized choice sets of landscape photographs from which they had to choose their most preferred one. One of these choices was then used to produce a consumer product with an imprint of the respective photograph (e.g., a mug, a T-shirt, etc.). Our results demonstrate that brain activity was modulated by the number of choice items available to the participants and by subjective perceptions about choice experience. While activity in some brain areas (such as the MOG, IOG, LG, SMA and PMd) increased linearly with the number of alternatives, activity in other brain regions (such as the NA, Caudate, ACC, MFG, and POG) followed an inverted U-pattern, with the increase of the choice set size. Areas exhibiting fMRI-activity which was correlated with the subjective choice set value were mapped within the posterior parietal cortex, which is known to respond in monkeys and humans to value and choice behavior. We further demonstrate how two other variables - “freedom” of choice and availability of a strongly preferred item - mediate neural representations of choice from multiple alternatives.

The findings are of significant theoretical and practical interest. Knowing how the structure of the consumer's environment and the computational processes people use affect choice behavior and satisfaction can allow marketers to develop tools that can benefit both consumers and companies.

Chapter 1

Satisfaction in Choice as a Function of the Number of Alternatives: When “Goods Satiate” but “Bads Escalate”[1]

1.1 Introduction

In today’s world, people face an embarrassment of riches in the form of the numbers of alternatives available for choice involving both small and large stakes, e.g., from chocolates and yogurts to health plans and pension schemes. And yet, although both economic theory and the psychological literature emphasize the benefits of more choice (see, e.g., Langer & Rodin, 1976; Zuckerman et al., 1978; Ryan & Deci, 2000), having many alternatives can be dysfunctional (Schwartz, 2000; 2004; Iyengar, Wells, & Schwartz, 2006). Rather than choosing from many options, people sometimes incur costs by foregoing or delaying decisions (Iyengar, Huberman, & Jiang, 2004). At the same time, some studies report greater satisfaction when choice involves limited numbers of alternatives (say six as opposed to thirty, Iyengar & Lepper, 2000).

[1] This work is done in collaboration with Robin M. Hogarth (ICREA & Universitat Pompeu Fabra). The research was supported by the Spanish Ministerio de Educación y Ciencia, grant number SEJ2006-14098 (to R. M. Hogarth). The authors are grateful for helpful comments from Barbara Fasolo, Ralph Hertwig, Barbara Kahn, Antonio Ladrón de Guevara, Abel Lucena, Rosemarie Nagel, Albert Satorra on earlier versions of this chapter. We express our special appreciation to José Antonio Aznar for his help in conducting the eye-tracking study.

Our goal in this paper is to illuminate how satisfaction from choice varies as a function of set size (i.e., the number of alternatives faced). We define satisfaction in two ways. One is satisfaction from the ultimate choice (i.e., "outcome satisfaction"); the other is satisfaction from the process of choosing itself (i.e., "process satisfaction"). Whereas most decision research correctly focuses on actual choices, satisfaction also merits attention. At the individual level, for example, Iyengar, Wells, and Schwartz (2006) have demonstrated that, even while doing better, so-called "maximizers" may feel worse because of "not always wanting what they get." In addition, organizations are typically interested in having satisfied clients or customers in the belief that satisfaction leads to further beneficial interactions.

We note, first, that at an empirical level, the set sizes examined in previous studies favoring choice are typically limited (up to 6 options) while the sets claimed to be demotivating are typically large (24-30 options) (Iyengar & Lepper, 2000; Kahn & Wansink, 2004). Curiously, little attention has been paid to choices that also involve intermediate numbers of alternatives (e.g., between 10 and 20 options). Indeed, we know of only one study. Shah and Wolford (2007) found that people were more likely to buy pens when confronted with intermediate numbers of alternatives (10 as opposed to 2 or 20). Second, at a theoretical level we note that authors of these empirical studies have not provided an *explicit* underlying rationale for the phenomena.

This paper provides and tests an explicit theoretical rationale for how satisfaction from choice varies as a function of set size. In particular, we emphasize not only levels of satisfaction associated with small and large set sizes but also what occurs at intermediate levels. We further indicate how characteristics of both individuals and tasks (e.g., types of choice alternatives) affect the relation between satisfaction and set size.

In addition to intrinsic theoretical interest, there are significant practical implications. From the marketing point of view it is crucial to understand how the structure of the consumer's environment (e.g., the number and characteristics of choice alternatives) affects satisfaction. Knowing this can allow marketers to develop tools that can benefit both consumers and companies. From the viewpoint of public policy, it is also important to understand how the relation between satisfaction and set size affects choice for major decisions such as pension schemes and health plans (see, e.g., Botti & Iyengar, 2006).

More specifically, we build on the idea that perceived benefits and costs (defined below) impact satisfaction – positively and negatively, respectively. Moreover both benefits and costs increase with the number of alternatives. However, we assume that the latter increase faster than the former (e.g., the benefits increase at a decreasing rate whereas the costs increase at an increasing rate). This assumption – that "goods satiate" while "bads escalate" (Coombs & Avrunin, 1977) – is not trivial and leads to predicting that satisfaction, which is defined as net benefits (i.e., benefits less costs), is an inverted U-shaped function of set size as illustrated in

Figure 1.1A

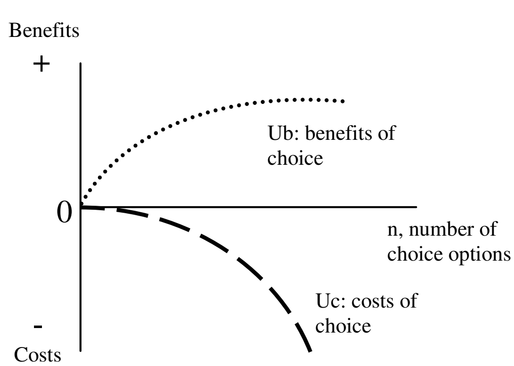

Figure 1.1B

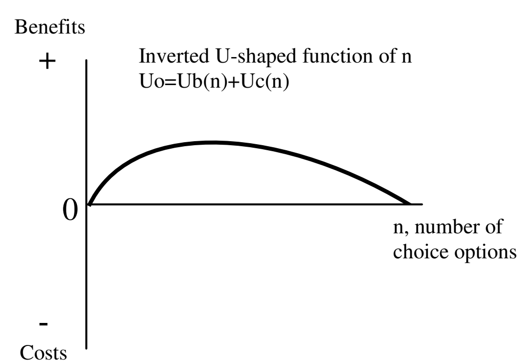

Figure 1.1: Satisfaction as a function of the number of alternatives.

Two clear implications of this function are that, first, greater outcome and process satisfaction will be experienced from choices made from intermediate as opposed to large or small set sizes; and second, changes in perceived costs and benefits will shift the position of the peak of the satisfaction function. For example, holding benefits constant, lower costs will shift the peak to the right. We emphasize the explicit nature of our theoretical rationale and, in particular, the predicted shape of the satisfaction function. More critically, it can be falsified empirically.

In our experimental work, we explicitly manipulate cognitive costs imposed on decision-makers by varying the visual attributes of choice alternatives and demonstrate how this affects the shape of the satisfaction function. We further emphasize the importance of *perceptions* of costs and benefits. Thus, even if the same choice set is viewed by different groups of people, the satisfaction function could reflect characteristics such as gender, culture, or knowledge. However, whereas the peak and position of the satisfaction function may change, there will still be an inverted-U relation between satisfaction and the number of alternatives.

This paper is organized as follows. The next section elaborates on the theoretical framework. This is followed by the presentation of five empirical studies. Study 1 explores the shape of the satisfaction function and examines the effect of costs due to visual characteristics of choices. The goal of Studies 2 (eye-tracking experiment) and 3 (questionnaire) is to illuminate the asymmetry in costs between visual attributes which contribute to the changes in the satisfaction function demonstrated in Study 1. Study 4 tests the influence of visual properties of alternatives on choice set attractiveness. Study 5 manipulates perceived psychic costs and demonstrates the effect of individual characteristics on the resulting function. We conclude by discussing implications.

1.2 Theoretical Framework

The proliferation of choice alternatives can be thought of as implying benefits and costs at two levels. One is at the level of the collective or society, the other at that of the individual. For the former, the existence of many alternatives is clearly advantageous in that it enables satisfying a multiplicity of different individual preferences. In addition, many choices can lead to the benefits of competition, e.g., lower prices and greater quality (Loewenstein, 1999). Moreover, perceived quality – and more purchases – can sometimes be achieved by companies that offer greater variety within brands (Berger, Draganska, & Simonson, 2007). Finally, the mere fact of having choice alternatives can enhance psychological well-being and thus also social welfare (see, e.g., Langer & Rodin, 1976).

At the individual level, however, the perceived benefits and costs of choice depend on both situational and psychological factors. One way of conceptualizing how these affect satisfaction is to specify how their associated benefits and costs vary as the number of alternatives in the choice set increases. This is illustrated in Table 1.1 where we, first, decompose situational and psychological costs, and, second, indicate how associated costs and benefits increase with set size.

We decompose situational factors into two components: time and economic. For the individual, we assume that, ceteris paribus, the cost of time to make a decision increases linearly with the number of alternatives examined. As to the economic factor – or more broadly the economist's notion of utility – we assume that benefits increase with the number of alternatives but at a decreasing rate, consistent with the notion of diminishing marginal utility (Horowitz, List, & McConnell, 2007).

Table 1.1: Benefits and costs of choice as a function of number of alternatives

Factors		**Benefits**	**Costs**
Situational	**Time**		Increasing (linear)
	Economic	Increasing (decreasing rate)	
Psychological	**Cognitive**		Increasing (increasing rate)
	Psychic	Increasing (decreasing rate)	Increasing (increasing rate)

At the psychological level, the cognitive costs of processing alternatives increase with the number of alternatives but at an increasing rate. This is in line with well-known limitations on human cognitive capacity (Newell & Simon, 1972).

At the psychic level, we postulate both benefits and costs. By the former we mean the positive affect that is generated by having more choice. In general, there is an attraction to having more alternatives (see, e.g., Iyengar & Lepper, 2000). As a thought experiment, contrast the emotional feelings experienced when entering a grocery store offering only a few options as opposed to entering a well-stocked competitor). Moreover, having more alternatives is associated with greater perceived decision freedom (Steiner, 1970; Reibstein, Youngblood, & Fromkin, 1975; Walton & Berkowitz, 1979), and gives people a feeling of autonomy and self-control thereby also facilitating intrinsic motivation (Zuckerman et al., 1978; Ryan & Deci, 2000).

By psychic costs we mean psychological costs that are emotional as opposed to cognitive in nature. These could be caused by discomfort due to uncertainty concerning preferences, lack of expertise, concern or regret about making an incorrect decision, emotional costs of making trade-offs, and so on (see, e.g., Loewenstein, 1999). Close consideration of the alternatives may also induce "attachment" to the options in the choice set such that people feel the "loss" of the items they have not chosen (Carmon, Wertenbroch, & Zeelenberg, 2003). Also, the more options foregone, the greater the post-choice discomfort experienced. Having too many alternatives may turn "freedom" of choice into "tyranny" (Schwartz, 2000).

Summing the situational and psychological benefits and costs of choice, our assumptions imply that both increase with set size. However, we assume that the benefits increase more slowly than the costs ("goods satiate" but "bads escalate," Coombs & Avrunin, 1977). In our experimental work, we do not test the separate shapes of the cost and benefit functions explicitly but rather focus on the "net" effect of the two.

Equating satisfaction with the net difference between benefits and costs, we predict that satisfaction is an inverted-U shaped function of the number of alternatives[2]. We therefore state our first hypothesis:

<u>Hypothesis 1</u>: Both outcome and process satisfaction are inverted U-shaped functions of the number of alternatives in the choice set.

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[2] Desmeules (2002) suggested that, when evaluating alternatives cognitively, the consumption experience might have an inverted U-shaped relation across set size. However, his proposition was neither formalized nor tested empirically

Effects of different visual presentations. An implication of the model in Table 1.1 is that changes in benefits and costs will change the satisfaction function. That is, it will maintain its inverted-U shape but maximum satisfaction will be shifted as appropriate.

Several studies suggest that the manner in which choice sets are presented can affect decisions, especially, when these are large. For example, in a seminal paper Miller (1956) noted that the organization of information into "chunks" or sequences facilitates information processing. More recently, Kahn and Wansink (2004) showed how organization affects consumers' perceptions of the variety of an assortment (i.e., perceived variety). For large choice sets, perceived variety is higher in organized sets; whereas for smaller sets, it is greater in disorganized sets. Huffman and Kahn (1998) demonstrated that, for high-variety sets, consumers were more satisfied (in terms of learning their own preferences), perceived less complexity, and were more willing to make choices when alternatives were presented in attribute- rather than alternative-based formats.

We suggest that satisfaction is also affected by the visual presentation of choice sets in that this impacts the cognitive costs imposed on decision-makers. Noting the implications of limitations in human visual abilities, Filin (1998) argues that people experience a feeling of discomfort and dissatisfaction in two "poorly organized" visual environments: "aggressive" environments (i.e., those with a great concentration of similar elements) and "homogeneous" environments (i.e., those with monotonic visual scenes, like plain white walls).

In our work, we consider the effect of two visual qualities – color and shape[3]. We suggest that if a choice set is large and the alternatives differ only in shape, the assortment has a "monotonic" look such that the individual faces a "homogeneous" visual environment that

[3] Our purpose here is not to determine how visual characteristics of separate objects influence decisions but rather how the visual characteristics of the entire set affect satisfaction.

imposes costs of discomfort (i.e., cognitive costs increase). Provision of colors, however, may resolve the problem of monotonicity by making the items more distinct thereby reducing costs for the human visual system.

Indeed, Spring, and Jennings (1993) claim that hue is recognized pre-attentively, while complex shape is a non-preattentive stimulus that requires more time to be processed. Thus, the detection of hue should not depend on the size of the set in which it is presented. On the other hand, since complex shape is a non-preattentive stimulus, the time and effort involved in processing shapes should be particularly high in larger sets[4].

We therefore propose that, when the set of alternatives is large, the cost of choice is higher for sets with alternatives differing in shape than for those differing in color. As a result, we expect people to be more satisfied when they are presented with large sets with options that differ in color as opposed to shape. In other words, the peak of the satisfaction function for colors will lie to the right of that for shapes. More formally, we state:

Hypothesis 2: Visual presentation of sets affects satisfaction. People experience higher satisfaction when the alternatives in large choice sets are different in color but not in shape. However, for small choice sets, they are equally satisfied when alternatives are presented in either different colors or shapes.

We emphasize that we limit our analysis and predictions in this paper to situations where people actually make choices as opposed to avoiding them. Moreover, we focus on situations where people do not have well-established preferences prior to choosing. In addition, we have simplified the discussion of the benefits and costs of different numbers of alternatives by ignoring possible interactions between different components. However, we believe that the

[4] Corbetta, Miezin, Dobmeyer, Shulman, and Petersen (1991) have also shown that attention to shape and attention to color can activate different regions of the brain.

simple structure implied by Table 1.1 should be investigated prior to considering such factors. This is the purpose of the present paper.

1.3 Study 1

The aim of Study 1 was to explore how satisfaction from choice varies as a function of the number of alternatives and to examine how changes in cognitive costs affect satisfaction. In this laboratory experiment, participants were given a picture representing a set of gift boxes with a certain number of alternatives (*5*, *10*, *15,* or *30*). They were asked to choose one gift box they would buy to pack a present for a friend and to report their levels of satisfaction. We manipulated cognitive costs imposed on individuals by varying two visual attributes of the gift boxes – color and shape.

1.3.1 Method

Choice sets. Choice sets consisted of *5*, *10*, *15*, or *30* gift boxes. The gift boxes differed from each other on two visual attributes: color and/or shape. Three types of sets were created representing gift boxes of: (1) the **s**ame **s**hape and **d**ifferent **c**olors (SSDC sets); (2) the **s**ame **c**olor and **d**ifferent **s**hapes (SCDS sets); (3) and **d**ifferent **c**olors and **d**ifferent **s**hapes (DCDS sets). The gift boxes did not contain anything and, except for visual attributes, were said to be identical. We refer to the SSDC and SCDS sets as "simple" since they vary on only one attribute and to the DCDS sets as "complex" since alternatives differ on two dimensions. No choice sets contained identical alternatives and all sets were organized (e.g., by shading of colors).

Participants and procedure. The 120 participants were students and professors at several universities in Barcelona, Spain (53% females, mean age of 23.7 years). All spoke English and received no financial remuneration.

The participants were randomly divided into 12 experimental groups formed by crossing two between-participant factors – number of choice options with four levels (*5, 10*, *15* or *30*), and three types of choice sets, SSDC, SCDS, and DCDS.

The experimenter invited one participant at a time into the experimental laboratory and showed him/her a picture representing a set of gift boxes. (Participants were unaware of the existence of other choice sets.) Each participant had to examine the picture and state which box s/he would buy to pack a present for a friend. After choosing, participants answered a paper-based questionnaire, evaluating satisfaction from the choice and providing demographic characteristics.

Dependent measures. Satisfaction can result from both the outcome of choice (i.e., the option chosen) and the process of choice itself (Steiner, 1980; Iyengar & Lepper, 2000). We therefore assessed both sources. We measured outcome satisfaction by participants' answers to the question "How much do you like the gift box you decided to pick?" Response to the question "How much did you enjoy making the choice (the decision process)?" was used to measure process satisfaction. We also asked two further questions. First, "Did you find it difficult to make your decision of which gift box to purchase?" Responses were provided on a scale ranging from 1 ("not at all") to 10 ("extremely"). Second, "Do you feel you had the right amount of options to choose from?" Responses were provided on a nine-point scale where 1

= “No, I had too few choice options,” 5 = “Yes, I had just the right number of choice options,” and 9 = “No, I had too many choice options.”[5]

1.3.2 Results

Satisfaction from the choice function. The results of Study 1 strongly support our first hypothesis. Self-reported satisfaction – both outcome and process – is an inverted U-shaped function of the number of alternatives as shown in Figures 1.2A and 1.2B. The participants reported lower outcome and process satisfaction from limited (*5*) and extensive (*30*) options, and higher satisfaction from medium-sized sets (*10* and *15* options). The *10*-option set was found to be the most satisfying. Difficulty of choosing also increased with the set size (see Figure 1.2C). Participants further believed that the “right number of options” was *10* or *15* (see Figure 1.2D). Recall that on this scale five was “ideal” with one being “too few” and nine “too many.” The *30*-option set was considered to be overwhelming, while the *5*-item set was perceived as offering too little choice. Outcome and process satisfaction showed significant positive correlation (r =0.41, $p < 0.001$).

We tested the inverted-U relationship between satisfaction and number of alternatives in two different ways: using regression analysis with the second degree polynomial and using ANOVA and t-tests. Both tests confirmed that satisfaction follows an inverted U pattern when the number of alternatives in the set increases.

[5] Most of the measures used in this experiment were similar to those used by Iyengar and Lepper (2000) in their study 3 which motivated the current research.

Figure 1.2A

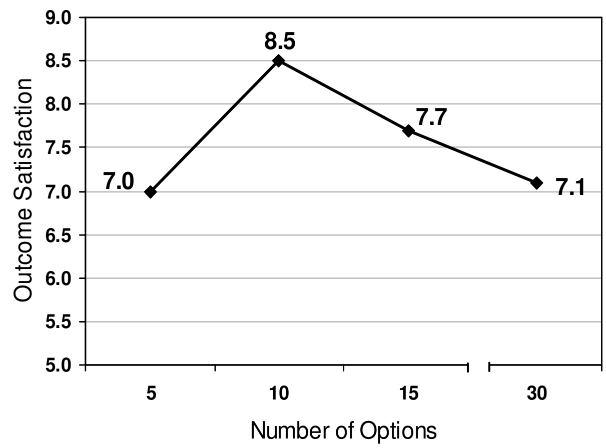

Figure 1.2B

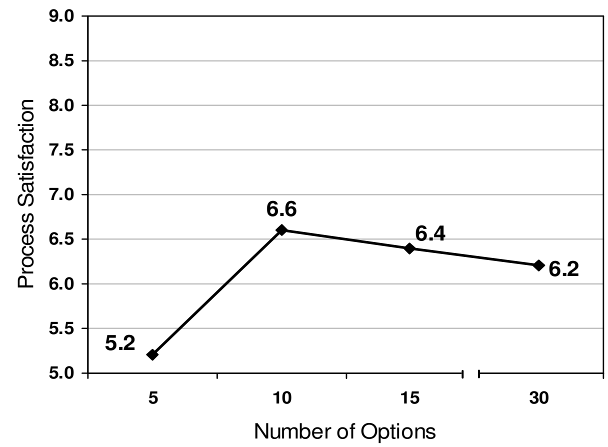

Figure 1.2C

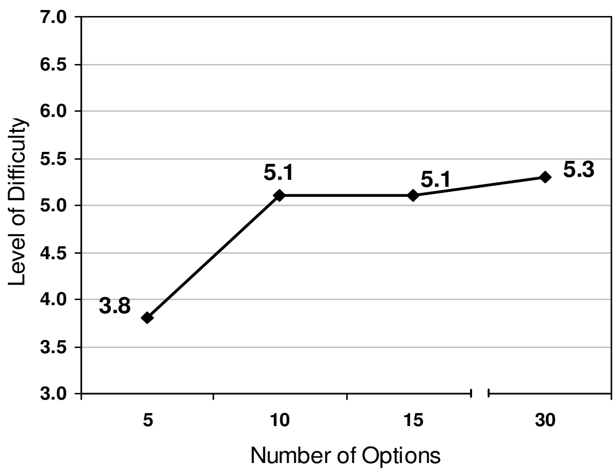

Figure 1.2D

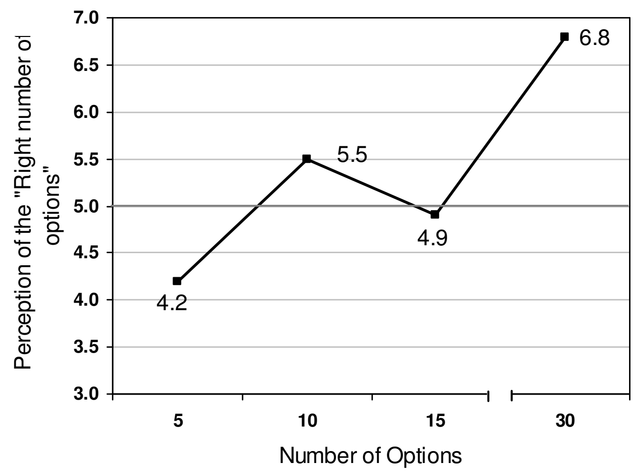

Figure 1.2: Dependent variables as a function of the number of alternatives in the choice set, Study 1. A. Outcome satisfaction; B. Process satisfaction; C. Difficulty level; D. Perception of the “right number” of options in the choice set.

First, outcome and process satisfaction were each regressed on the number of alternatives (represented by both linear and quadratic terms) controlling for visual characteristics of the sets. Both models –outcome and process satisfaction models – were significant [$F(4, 115) = 6.33$ $p = 0.000$; $F(4, 115) = 4.49$, $p = 0.002$, respectively]. This analysis supported the inverted U-shape relation between satisfaction and set size in that- in both the outcome and process satisfaction models - the linear ($t = 3.21$, $p = 0.002$; $t = 3.07$, $p = 0.003$, respectively) and quadratic ($t = -3.51$, $p = 0.001$; $t = -2.87$, $p = 0.005$, respectively) terms were significant with appropriate signs. Participants facing SSDC sets also expressed significantly higher outcome and process satisfaction than those facing DCDS sets ($t = 3.37$, $p = 0.001$; $t = 2.65$, $p = 0.009$, respectively).

Second, ANOVA (see Table 1.2) indicates that the size of the choice set significantly affects satisfaction for all four dependent measures. Statistical tests of the nature of these differences (i.e., whether satisfaction functions have inverted U shapes) are presented in Table 1.3. This shows, for example, that for "outcome satisfaction" (Figure 1.2A), the mean satisfaction for *10* options (8.5) is significantly greater than both those for *5* and *15* options (i.e., 7.0 and 7.7, respectively), and that satisfaction for *15* options significantly exceeds that for *30* (i.e., 7.7 vs. 7.1).

Visual presentation. Study 1 also aimed to test whether two visual attributes – color and shape – affect satisfaction from different set sizes, a question motivated by our assertion that colors imply less cognitive costs than shapes. We therefore analyzed the responses of the 80 participants who faced SCDS and SSDC sets.

Table 1.2: Significance of the set size effect on dependent variables

Dependent variable	Statistics		
	Study 1	Study 5	
		Unaware group	Aware group
Outcome Satisfaction	F(3, 116) = 8.92 p = .000	F(3, 116)= 3.35 p = .022	F(3, 116)= 2.90 p = .038
Process Satisfaction	F(3, 116)= 4.07 p = .009	F(3, 116) = 2.22 p = .089	F(3, 116) = 2.84 p = .041
Difficulty level	F(3, 116) = 2.77 p = .045	F(3, 116) = 4.41 p = .006	F(3, 116) = 0.66 p = .580
Perception of the right number of options	F(3, 116) = 10.21 p = .000	F(3, 116)= 2.78 p = .044	F(3, 116)= 3.98 p = .010

Table 1.3: Increases/ declines of means among choice sets with different numbers of alternatives

Measure	Sample	5 vs 10	5 vs 15	5 vs 30	10 vs 15	10 vs 30	15 vs 30
Satisfaction from the gift box picked	Study 1	+1.53***	+0.73**	+0.13	-0.80**	-1.40***	-0.60*
	Study 5 Unaware group	+0.14	+1.20***	+0.60	+1.06**	+0.46	-0.60
	Study 5 Aware Group	+1.20**	+1.40*	+0.60	+0.20	-0.60	-0.80
Satisfaction from the decision-making process	Experiment 1	+1.37***	+1.23***	+0.97**	-0.14	-0.40	-0.26
	Study 5 Unaware group	+0.37	+1.40**	+0.60	+1.03*	+0.23	-0.80
	Study 5 Aware Group	+1.03*	+1.63***	+1.73***	+0.60	+0.73	+0.13
Difficulty level	Experiment 1	+1.27**	+1.27**	+1.47**	0	+0.20	+0.20
	Study 5 Unaware group	+1.70**	+0.27	+1.88***	-1.43**	+0.17	+1.6**
	Study 5 Aware Group	+0.10	+0.80	+0.64	+0.70	+0.54	-0.16

*** $p < .01$
** $p < .05$
* $p < .10$

ANOVA supported our second hypothesis. Participants facing large sets (i.e., *30* options) with alternatives varying in color reported significantly higher outcome satisfaction [$F(1, 72) = 10.93$, $p = .002$] than those encountering sets with items differing in shape (Figure 1.3A). For the small and medium-sized sets, however, this difference was not significant [$F(1, 72) = 0.95$, $p = .334$; $F(1, 72) = 3.06$, $p = .084$; $F(1, 72) = 0.95$, $p = .334$ for *5*-, *10*- , and *15*-option sets respectively]. Moreover, the participants facing SSDC sets were significantly more satisfied with the process of choosing than those who encountered SCDS sets over the *entire* range of set sizes [$F(1, 75) = 4.15$, $p = .045$] – see Figure 1.3B.

Visual format also affected participants' beliefs about the right number of options in the set. When facing SSDC sets, the participants believed that *15*- or even *30*-option sets contained "about the right number of options" [$F(1, 72) = 1.65$, $p = .203$; $F(1, 72) = 1.65$, $p = .203$ respectively]. However, *30* options in the SCDS sets were viewed as "more than the right amount" [$F(1, 72) = 26.40$, $p = .000$] – see Figure 1.3C.

Our results and analysis demonstrate that satisfaction is an inverted U-shaped function of the number of alternatives for the SCDS sets. For the SSDC sets, however, this inverted U-shape relation is not evident as the function did not decrease significantly after the peak. To verify whether satisfaction would fall if the size of the SSDC set would become "too large," we conducted an additional treatment (with procedure identical to the others) where 34 new participants faced an extensive SSDC set of 54 gift boxes. Results indicated that, from the *30* to *54* option set, both outcome and process satisfaction did indeed decrease significantly (from 8.3 to 7.1 [$t = -2.31$, $p = .024$], and from 7.1 to 5.2 [$t = -2.52$, $p = .014$], respectively – see Figures 1.3A and B).

Figure 1.3A

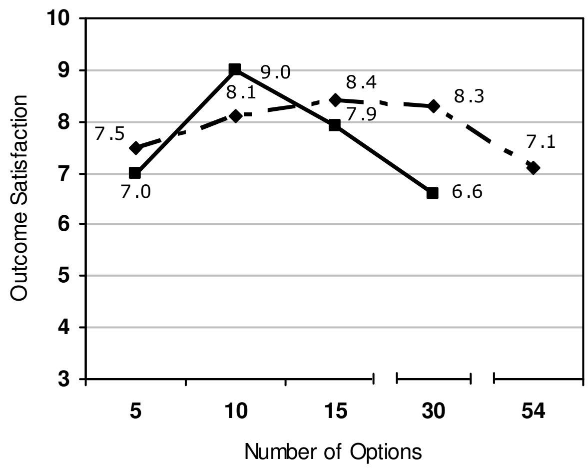

Figure 1.3B

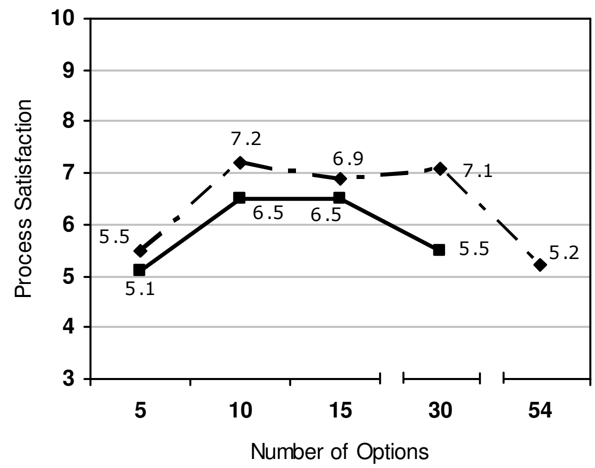

Figure 1.3C

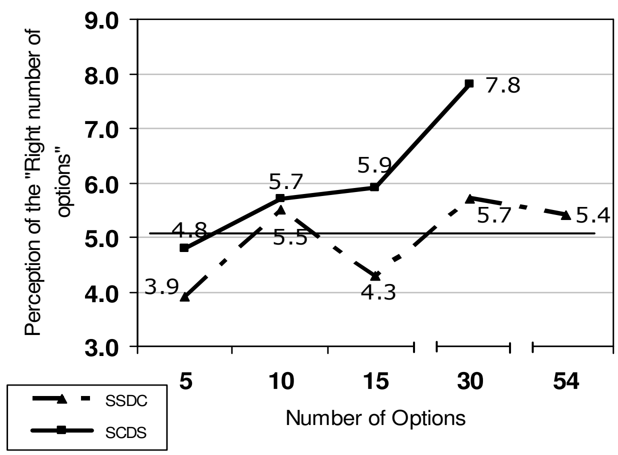

Figure 1.3: Effect of different visual presentation, Study 1. A. Outcome satisfaction; B. Process satisfaction; C. Perception of the "right number" of options.

Gender and complexity. ANOVA revealed significant gender differences in outcome satisfaction (controlling for set size). Compared to men, women reported higher outcome satisfaction [$F(1, 115) = 4.07$, $p = .046$].

ANOVA also showed that participants facing simple sets (i.e., with items differing in one attribute only) were significantly more satisfied with the outcome than those encountering complex choice sets (i.e., with items differing in two attributes) controlling for set size [$F(1, 115) = 9.81$, $p = .002$]. No significant gender or complexity effects were found for the other dependent variables. For detailed results on gender and complexity effects see Appendices 1.A and 1.B.

1.3.3 Discussion of Study 1

Study 1 demonstrated that satisfaction with both outcome and process is an inverted U-shaped function of the number of items in the set. In other words, the data support Hypothesis 1.

Study 1 also supported Hypothesis 2 in that the peak of the function for colors was shifted to the right. This, we had argued, was due to lower cognitive costs for colors as opposed to shapes. However, we did not verify independently that the cognitive costs associated with colors and shapes differed. Therefore, in Studies 2 and 3 (below), we specifically investigate these costs using questionnaire and eye-tracking methodologies.

In Study 1 outcome and process satisfaction were positively correlated. However, whereas outcome satisfaction in the 30-option case decreased to a level comparable to the 5-option case, process satisfaction was significantly greater for the 30- than for the 5-option sets. These results are in line with previous research. Iyengar and Lepper (2000) demonstrated that when selecting and sampling a chocolate from either extensive (30 options) or limited (6 options) choice sets, subjects enjoyed the decision-making process more but, at the same time, reported lower satisfaction with selection in the 30- than in the 6-option condition. Study 1 demonstrated that process satisfaction does not increase indefinitely. Rather, it decreases when the choice set size is made significantly large. In our case, process satisfaction in the 54-item SSDC set decreased to the level of that in the 5-option case.

Study 1 suggests that the satisfaction function may depend on gender. For males the function lies below that of females. Two explanations come to mind. First, there is evidence that women are used to paying more attention to detailed information than men and this habit might lower the costs of choice in some tasks (Meyers-Levy & Maheswaran, 1991). Second, females may simply care more about items such as gift boxes than males. For a different kind of choice (e.g., beer or cell telephones), one might find the reverse effect. Whether gender effects can be generalized across different conditions remains unclear and is an interesting topic for further research.

The findings of Study 1 also demonstrated that participants reported lower outcome and process satisfaction when encountering complex rather than simple sets over the entire range of set sizes. This finding is consistent with our model. As the complexity of the sets increases, both the psychological costs and benefits rise. If the shift in costs is greater than that in benefits, the resulting satisfaction function shifts downwards. However, because we only observed "net effects" of perceived benefits and costs, we were unable to test this implication explicitly. The separation of effects of costs and benefits is critical for understanding the underlying processes of choice and should be investigated in further research.

The finding that the peak of the satisfaction function for colors was positioned to the right of that for shapes was consistent with our assertion that colors impose less cognitive costs than shapes. However, this assumption was not explicitly tested in Study 1. Moreover, implicit in the design of Study 1 are the assumptions that participants' preferences for colors and shapes are equally well-established and that individual boxes in the SSDC sets were as attractive as those in the SCDS sets. Better established preferences for colors as opposed to shapes, as well as the presence of more appealing colors than shapes in large sets, could provide two alternative explanations for the rightward shift of the satisfaction function peak for the SSDC sets.

We therefore explicitly designed two studies to test the following hypothesis and rule out these two alternative explanations:

Hypothesis 3: The cognitive costs for alternatives differing in shape are greater than those for alternatives differing in color.

1.4 Study 2

The primary goal of this study was to test whether cognitive costs for options differing in shape are higher than those for options differing in color and to illuminate participants' evaluations of individual boxes. We conceptualized the cognitive costs of choosing as having two components: (1) "preference uncertainty" costs incurred when people decide how much they like what they have observed (i.e., when establishing preferences); and (2) "processing" costs that involve perceiving the objects that are evaluated. We also aimed to tease apart these two types of cognitive costs and to verify whether they differ depending on color and shape.

In this study participants had to examine and evaluate – in terms of liking – 120 gift boxes, one at a time. Time, individual ratings of the boxes and eye-movements of participants were recorded while they examined the boxes and made their judgments (for more detailed discussion of eye-tracking methodology, see Chandon, Hutchinson, Bradlow, & Young (2007).

1.4.1 Method

Procedure, participants and stimuli. Fifteen students at a university in Barcelona, Spain participated (27% males, mean age of 25.6 years). Each received 10 euro for participating. One at a time, each participant had to examine sequentially pictures of gift boxes on a computer screen and state how much s/he liked the boxes (for packing a present for a friend). Each participant was told to imagine that any present would fit into the boxes. The computer screen participants faced was divided into halves: on the left was the image of the box; on the right, a 10-point rating scale. An example of the computer screen is presented in Figure 1.4.

The boxes were presented to participants one at a time and were identical to those in Study 1. Participants had a maximum of seven seconds[6] to examine each box and to rate how much they liked it. However, they could use less time and proceed to the next trial.

Each participant was presented with four blocks of 30 boxes (i.e., 30 trials) each, and thus had to make 120 judgments in total (i.e., 4 x 30). Within one block, boxes varied on only one attribute – color or shape. Each participant faced two blocks with boxes differing in color, and two blocks with boxes differing in shape. For example, in the first block ("**S**ame **C**olor **D**ifferent **S**hapes" – SCDS – condition) the participant would have to evaluate 30 boxes one at a time that would be blue in color, but of different shapes. In the second block, the same shapes as in the first block would be presented to the participant in the color red (SCDS

[6] Note that Reutskaja, Pulst-Korenberg, Nagel, Camerer, and Rangel (2008) show that participants are able to make high quality decisions from 16 alternatives even within three seconds. In the current experiment, participants had seven seconds to evaluate each alternative.

condition). In the third block, the participant would face 30 oval boxes of different colors ("**S**ame **S**hape **D**ifferent **C**olors", SSDC condition), and so on. The order of the blocks as well as that of presenting the stimuli was randomized.

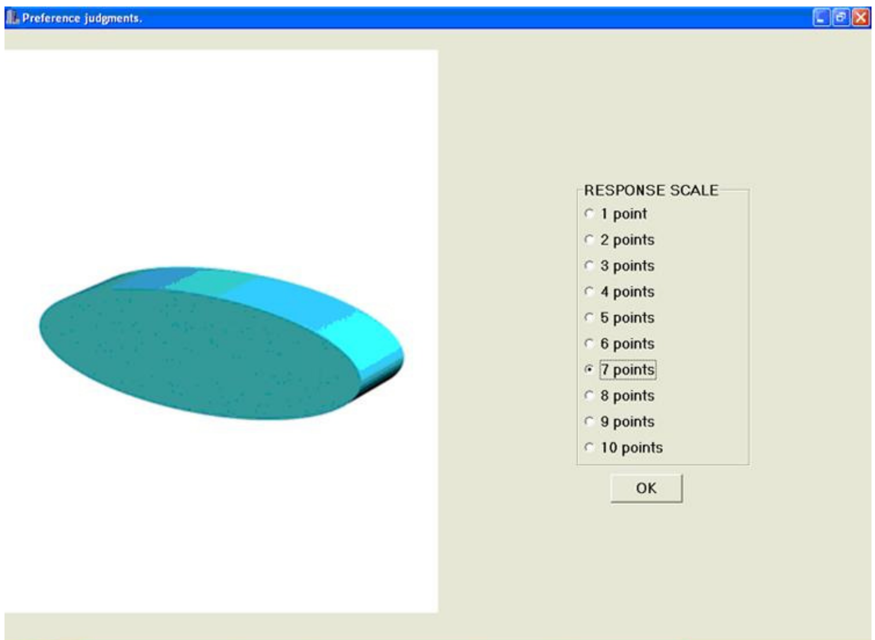

Figure 1.4: Sample of a screen participants faced in the eye-tracking experiment.

Participants' eye-movements were tracked while they examined and evaluated the images of the boxes. Prior to viewing the stimuli, each participant went through a calibration procedure that required looking at moving dots on the screen, and through a short training session during which they evaluated six boxes that were not used in the actual study. We used the VSG2/5 Workstation & Videoeyetracker which recorded the positioning of the eye gazes on the screen and pupil dilations of participants every 20 milliseconds.

Dependent measures. We used both behavioral and eye-tracking measures.

Behavioral measures. We assessed the total cost of processing and determining preferences about each box by measuring the total time spent on each trial. The average total time spent on processing the boxes and establishing preferences in the SCDS condition was then compared to that in the SSDC condition.

We also assessed how much participants liked each box by their responses to the question "How much do you like the gift box presented on the screen?" Responses were given on a 10-point scale ranging from 1 ("not at all") to 10 ("extremely). We then compared the average liking ratings given to the boxes in the SCDS and SSDC conditions.

Eye-tracking measures. The eye-tracker recorded the eye-movements of the participants every 20 ms while they were processing and evaluating the images. This allowed separating processing from preference uncertainty costs. Specifically, processing costs were measured by the time participants spent looking at the part of the screen where the image of the box was presented for the first time, while preference uncertainty costs were measured by the time spent on further gazes at the image of the box as well as at the part of the screen with the scale.

1.4.2 Results

Behavioral data. Each of fifteen participants had to make 120 choices in total. We dropped one trial (of one participant) from the analysis as the corresponding data were not recorded for technical reasons. As a result, we analyze data obtained from 1,799 (i.e., 120 x 15-1) trials.

The results strongly support Hypothesis 3. On average, participants spent 3.13 seconds per trial. The average total time spent per trial was 253 ms higher in the SCDS than in the SSDC blocks. To test the significance of this effect in the presence of high individual variability, we regressed response time on dummy variables for both type of blocks and individual participants. This revealed a significant block effect ($t = 3.54$, $p < .001$) controlling for individual effects – see Table 1.4. In short, the total costs of determining preferences and processing alternatives differing in shape are greater than for those differing in color.

Table 1.4: Regression analysis of the effect of attribute (color/shape) on response time

	Dependent Variable	
	Response Time (ms)	St. Error
Color	-252.78	71.32***
Participant1	-1,278.18	0.00***
Participant2	202.66	0.00***
Participant3	-912.66	0.00***
Participant4	-215.56	0.30***
Participant5	-1,428.32	0.00***
Participant6	-617.56	0.00***
Participant7	-343.80	0.00***
Participant8	-795.25	0.00***
Participant9	-712.42	0.00***
Participant10	-810.35	0.00***
Participant11	-844.23	0.00***
Participant12	-18.80	0.00***
Participant13	-797.93	0.00***
Participant14	477.47	0.00***
Constant	3,793.85	35.66***
Observations	1799	
R-squared	0.44	

Notes:
(1) *** $p < .01$; ** $p < .05$; * $p < .10$
(2) Color is the dummy: Color=1 if box is in the SSDC block, and Color=0, if box is in the SCDS block
(3) Participant_i is the dummy indicating participant i ($1 \leq i \leq 15$).

Consistent with our assumption, the liking ratings assigned to items in the SCDS blocks did not differ significantly from those in the SSDC blocks (t = 1.89, p = .08, with liking ratings of items in the SSDC blocks being slightly lower than those in the SCDS blocks). We tested this effect by regressing the liking rating of the box on block type controlling for individual effects, see Table 1.5.

1.4.3 Eye-tracking data

We excluded the eye-tracking data of three (of the fifteen) participants because of unacceptable rates of erroneous trials (more than 20%). In addition, several trials were not properly recorded due to technical reasons and had to be deleted. As a result, our analysis is based on the data from 1,283 trials.

Results show that time for processing items was 188 ms higher for the SCDS blocks than for the SSDC blocks. To test this effect, we regressed time first spent processing the image on block type controlling for individual effects. This was significant (t = 3.72; p < .010) – see model on left of Table 1.6. However, when subsequent time spent looking at the image and scale was regressed on block type, there was no significant effect (t = 1.10; p = .294) – see model on right of Table 1.6.

Overall, the results suggest that the processing costs for colors are greater than those for shapes, but “preference uncertainty” costs are equal for the two attributes. To test further the finding regarding preference uncertainty costs, we conducted a questionnaire study.

Table 1.5: Regression analysis of the effect of attribute (color/shape) on liking rating of the image

	Dependent Variable	
	Liking Rating of the Image	St. Error
Color	-0.62	0.33*
Participant1	0.71	0.00***
Participant2	-1.13	0.00***
Participant3	-0.57	0.00***
Participant4	1.04	0.00***
Participant5	-0.79	0.00***
Participant6	1.04	0.00***
Participant7	-2.88	0.00***
Participant8	-1.26	0.00***
Participant9	1.62	0.00***
Participant10	-1.08	0.00***
Participant11	1.08	0.00***
Participant12	-0.66	0.00***
Participant13	0.37	0.00***
Participant14	0.59	0.00***
Constant	5.80	0.17***
Observations	1797	
R-squared	0.22	

Notes:
(1) *** $p < .01$; ** $p < .05$; * $p < .10$
(2) Color is the dummy: Color=1 if box is in the SSDC block, and Color=0, if box is in the SCDS block
(3) Participant_i is the dummy indicating participant i ($1 \le i \le 15$).
(4) Two trials in which participants failed to indicate their ratings were coded as missing.

Table 1.6: Regression analysis of the effect of attribute on time spent on processing the image and defining one's preferences.

	Dependent variable			
	Time first spent processing the image (ms)	St. Error	Subsequent time spent on looking at the image and scale	St. Error
Color	-188.38	51.23***	-59.77	54.25
Participant1	-359.88	1.09***	-899.31	0.47***
Participant2	-311.34	0.08***	-745.09	0.08***
Participant3	-193.80	0.88***	-84.94	0.94***
Participant4	-476.75	0.88***	-382.33	0.94***
Participant5	-248.46	5.86***	11.23	6.20*
Participant6	-265.79	8.32***	-794.99	8.81***
Participant7	-229.20	8.37***	-570.11	8.86***
Participant8	-243.99	2.45***	-714.69	2.60***
Participant9	-12.41	0.00***	-41.83	0.00***
Participant10	-264.13	0.43***	-718.32	0.46***
Participant11	217.83	0.22***	-2.36	0.23***
Constant	908.36	25.40***	2,602.91	26.90***
Observations	1283		1283	
R-squared	0.33		0.26	

Notes:

(1) *** $p < .01$; ** $p < .05$; * $p < .10$

(2) Color is the dummy: Color=1 if box is in the SSDC block, and Color=0, if box is in the SCDS block

(3) $Participant_i$ is the dummy indicating participant i ($1 \leq i \leq 15$).

(4) Analysis excludes data for which either processing or preference uncertainty costs were not recorded (3.2% of trials).

1.5 Study 3

In Study 3, we sought to understand people's perceived preferences for colors and shapes in general as well as in the context of gift boxes. For this we used a questionnaire.

1.5.1 Method

Procedure. The questionnaire assessed participants' preferences for colors and shapes. Participants had to state what color/shape they liked most both overall (i.e., answer the question "What is your favorite color/shape?") and in the context of gift boxes (i.e., answer the question "If you think of the ideal gift box: What color/shape would you prefer this box to be, which you would receive/give from/to a friend)?")[7]. Participants could either state their preferred color or shape, or respond "I do not know."

Participants. Respondents were 106 students at a university in Barcelona, Spain (58% females, mean age of 19.4 years). Each received 3 euro for participating.

Dependent measures. We calculated the number of "do not know" responses to questions regarding color and shape preferences both overall and in the context of the gift boxes. We assume that the greater the number of "do not know" responses, the less defined are preferences for colors or shapes.

1.5.2 Results

In general, participants had better established preferences for colors than for shapes.

[7] In fact, participants were asked many questions. Here we simply report responses that are pertinent to this paper.

More participants failed to report a favorite shape as opposed to a favorite color (t = 4.97, p <0.001) (Responses were coded as "1" if participant responded "I don't know", and "0" otherwise). However, in the context of gift boxes, these differences disappeared. Participants had equally well determined preferences for colors and shapes independently of whether the box was to be given or received (t = 0.22, ns, t = 0.00, ns, respectively).

1.5.3 Discussions of Studies 2 and 3

We used behavioral and biological measures to explain the asymmetry between the two attributes of interest – color and shape. First, Study 2 demonstrated that cognitive costs – as measured by response times – were greater for shapes than for colors. This is consistent with our theoretical framework and can explain the shift of the peak of the function in Study 1. Second, Study 2 revealed that this difference in time is attributed to processing rather than preference uncertainty costs. In Study 2 participants processed items differing in color in less time than those differing in shape.

Third, the eye-tracking data showed that the time spent on defining preferences regarding the boxes did not differ between the SCDS and SSDC conditions. This finding was replicated in the questionnaire, which demonstrated that people have equally well established preferences for colors and shapes in the context of gift boxes. These results support the notion that the shift of the peak of the satisfaction function in Study 1 cannot be explained by differences in preference uncertainty costs, that is, for defining preferences. Nor can the shift be explained by the fact that items in the SCDS sets were less appealing to the participants. Indeed, the eye-tracking study demonstrated that items presented in the SCDS and SSDC sets were seen as equally attractive by participants (with, if anything, a slight – significant at 10% – liking bias for the SCDS images).

Our eye-tracking study and questionnaire have important theoretical and practical implications. First, measuring the cognitive costs for the two different attributes served as an empirical verification of our theoretical framework. We demonstrated that colors are less taxing than shape thereby inducing the shift of the satisfaction function found in Study 1.

Second, comparison between two widely used visual attributes – color and shape – has practical implications for people offering choices. The results suggest that presenting alternatives of large sets in different colors can create "comfortable" visual environments thereby attracting more people, and positively influencing outcome and process satisfaction. As a result, people may be able to obtain high benefits from larger set sizes without losing satisfaction.

Study 1 demonstrated that visual presentation of assortment influences satisfaction. More specifically, participants reported significantly higher levels of satisfaction when the alternatives in the large choice sets were different in color but not in shape (Hypothesis 2). However, does this mean that the sets with alternatives different in color are also more attractive than those that vary in shape? This question becomes relevant when people choose between different sets of offerings rather than selecting an item from a given set.

As a corollary to Hypothesis 2, therefore, we suggest that since visual "comfort" is more pleasing for the eyes (and less "costly" to process), one should also expect large SSDC sets to be more appealing than large SCDS sets. Also – and once again – since the costs of choice from small sets are not unduly taxing, we would not expect such effects with small sets. More formally, we state:

Hypothesis 4: Visual properties of the set affect its attractiveness. More people are attracted to large sets when alternatives differ in color as opposed to shape. No such effects exist for small sets.

We conducted Study 4 to test this hypothesis

1.6 Study 4

1.6.1 Method

Procedure. The design of Study 4 was similar to that of Study1. The main difference was that, first, participants had to decide which of the sets of gift boxes they liked the most: that in “shop A” which offered gift boxes varying in shape (SCDS set) or that in “shop B” which offered boxes differing in color (SSDC set). Participants were given pictures representing each of the two sets. The choice sets were identical to those of Study 1. Both sets offered to a particular individual were of the same size involving *5*, *10*, *15*, or *30* alternatives.

Participants were 48 undergraduate students (mean age of 19.2 years, 54% females) at a Spanish University. Participants were not remunerated. Groups of 12 participants were assigned at random to each of four groups evaluating the different-sized options.

First, participants had to choose which choice set – shop A or B – they preferred and answer a questionnaire assessing their satisfaction with each set and the difficulty of choosing between them. Second, the participants were left with the picture of the choice set they had selected and asked to choose a gift box and complete the same questionnaire as in Study 1.

Measures. First, we simply counted the numbers of participants who chose each “shop” for the different set sizes. Second, we assessed participants’ satisfaction with each choice set and the difficulty of choosing between them by asking “How much do you like the assortment in shop A?”, “How much do you like the assortment in shop B?”, and “How difficult was it for you to decide to which shop to go?” Responses were provided on a 10-point scale ranging from one (“Not at all”) to 10 (“Extremely”). Third, satisfaction measures concerning choices of boxes were identical to those used in Experiment 1.

1.6.2 Results

When facing medium or large choice sets (i.e., sets containing *10*, *15* or *30* alternatives) 25 out of 36 participants preferred the options in shop B where boxes varied in color but not in shape thereby indicating that the former are more attractive [$p(x \leq 11) = .025$, binomial test]. For small sets (5 options), there was no significant difference [$p(x \leq 5) = .387$]. However, this lack of a significant difference could simply be due to the small sample of participants (12) facing *5*-alternative sets. We therefore recruited 19 additional participants for a *5*-option set treatment of this study. Results showed that of the 31 participants who faced *5*-alternative sets, 15 preferred the SSDC sets. In other words, there was no significant difference in choices between the SCDS and SSDC sets [$p(x \leq 15) = 0.500$, binomial test].

Finally, participants reported greater satisfaction levels from the SSDC than SCDS sets when the number of alternatives in the set exceeded 10 ($t = 1.98$, $p = .056$), but similar satisfaction levels for *5*-option sets ($t = 0.98$, $p = .381$).

1.6.3 Discussion of Study 4

The results of Study 4 provide support for Hypothesis 4. Sets of alternatives differing in color were more attractive than those differing in shape when the sets were large, while both were seen as equally appealing when set size was small. This is consistent with the arguments provided above. Namely, the costs of processing alternatives differing in color are lower for the human visual system than those associated with shape.

Study 1 demonstrated that visual properties of the alternatives in the set affect perceived costs and benefits and therefore influence the peak of the satisfaction function. However, can individual characteristics also affect perceived costs and benefits of choice? We took the opportunity to investigate this issue in a slightly different experimental setting.

In our initial setting, participants face a given set of choice alternatives and are unaware of the possible existence of other sets. However, would satisfaction be affected if participants were aware of the existence of choice sets different from theirs? Clearly, people do not only engage in evaluating trade-offs between the alternatives they face, but also compare their own possibilities with those of others. Indeed, as originally demonstrated by Festinger (1954), when objective measures are not available, people tend to judge their own possibilities by comparison with those of others. Thus, if when presented with a set of alternatives, a person is made aware of the existence of other alternatives, he or she may well feel at a disadvantage and thereby incur psychic costs.

The framework in Table 1.1 suggests how awareness about choice sets different from one's own will affect the relation between satisfaction and set size. Specifically, the psychic costs incurred before even viewing the choice set would imply a downward shift of the cost curve by a fixed amount and thus also a downward shift of the resulting satisfaction function. More formally, we hypothesize:

Hypothesis 5: Individuals, who are aware of the existence of choice sets different from theirs and from which they cannot choose, are less satisfied with their choice than those who do not possess such knowledge.

To test this hypothesis we conducted Study 5.

1.7 Study 5

1.7.1 Method

Study 5 involved two groups of participants. In one, the treatment was identical to the experiment in Study 1. We call this the "unaware" group. The treatment of the second group – the "aware" group – was identical but with two exceptions. First, unlike Study 1, where only one participant at a time was invited into the experimental laboratory, several participants followed the experimental procedure simultaneously in the same room. Second, participants of Study 5 were explicitly told that their colleagues had been given choice sets differing from their own in size and visual properties of the alternatives. The participants were unaware how many different choice sets there were, which choice set was larger or smaller and could only see the sets offered to their colleagues from a distance. After being given a picture representing a choice set, participants followed the same procedure as in Study 1.

Participants. 240 students and professors (50% females, mean age of 22.7 years) from several universities in Belarus (66%) and Ukraine (34%) took part in the experiment. They received no financial remuneration. Study 5 was conducted in Russian.

1.7.2 Results

Consistent with the findings of Study 1, outcome satisfaction was found to follow an inverted U-shape for the unaware group – see Figure 1.5 and Tables 1.2 and 1.3.

Compared to the unaware group, the aware participants were less satisfied with their ultimate choice ("awareness" dummy $F(1, 235) = 7.18$, $p = .008$), and with the process of choosing ($F(1, 235) = 4.96$, $p = .027$), thereby providing support for Hypothesis 5. That is, the satisfaction function for aware participants was shifted downwards in comparison with the unaware group.

We also explored the influence of "cultural background" on the four variables of interest by comparing the responses of "unaware" group of study 5 and those of participants in Study 1.

Though the satisfaction function of the Eastern European "unaware" group had an inverted U-shape, participants from Belarus and Ukraine reported the highest satisfaction with the gift box picked from *15*- and *30*-option sets whereas Western Europeans (group in Study 1) were most satisfied with the box chosen from medium-sized sets. The peak of the function, therefore, was shifted toward a greater number of alternatives in the Eastern European sample [$F(4, 232) = 4.10$, $p = .003$, Chow test], sets with *15* options being seen as the most satisfying. Interestingly, the Eastern European participants also reported the lowest difficulty levels when choosing from such sets, and considered that the *15*-option set included exactly the "right number of boxes."

Gender and complexity. We found significant gender and complexity effects for several dependent variables in the Eastern European unaware group (see Appendices 1.A and 1.B). Eastern European females reported significantly higher satisfaction levels than men both with the box picked and with the decision process. Across all set sizes, satisfaction with the box picked was lower for participants facing complex as opposed to simple sets.

Figure 1.5A.

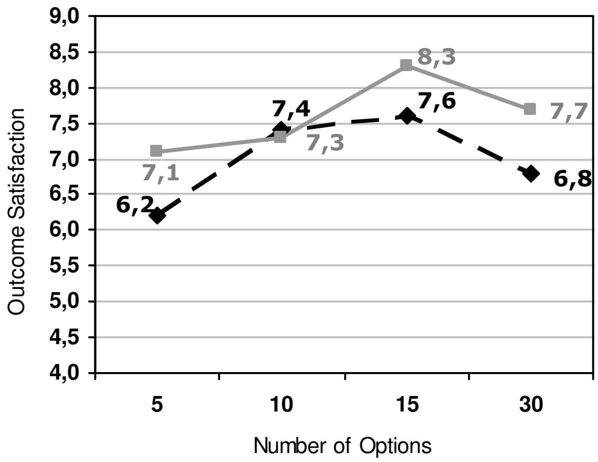

Figure 1.5B

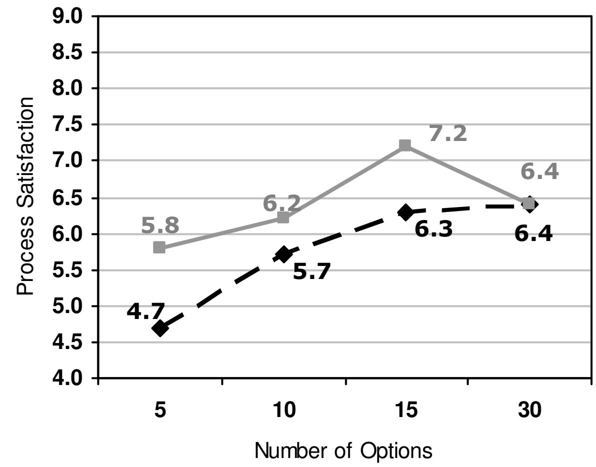

Figure 1.5C

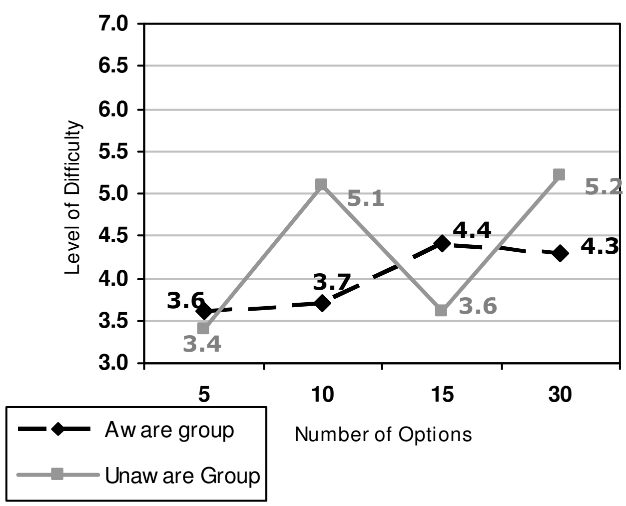

Figure 1.5D

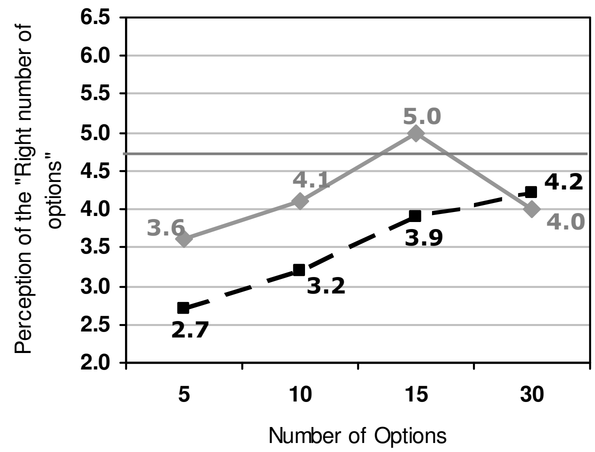

Figure 1.5: Effect of "awareness" on choice experience, Study 5. A. Outcome satisfaction; B. Process satisfaction; C. Difficulty level; D. Perception of the "right number" of options in the choice set.

Visual presentation. In line with the findings of Study 1 (and Hypothesis 2), ANOVA yielded differences in satisfaction of the Eastern European “unaware” participants due to the visual layout of alternatives. Eastern Europeans reported higher satisfaction both with the gift box picked [$F(1, 72) = 4.02$, $p = .049$], and with the decision process [$F(1, 72) = 3.13$, $p = .081$], when facing large sets (*30* options) in the SSDC as opposed to SCDS format. Moreover, participants felt they had fewer options when facing SSDC sets rather than the same sized SCDS sets [$F(1, 75) = 8.26$, $p = .01$] – see Figure 1.6.

1.7.3 Discussion of study 5

The outcome satisfaction curve of the unaware participants replicated the results of Study 1 thereby providing additional support for Hypotheses 1 and 2. Consistent with Hypothesis 5, the results of Study 5 also demonstrated that knowledge of the existence of choice sets different from one’s own decreases both process and outcome satisfaction. As argued above, the effect of telling participants explicitly that others can choose from different sets imposes additional “fixed” psychic costs even before the choice is made. Holding benefits constant, this initial increase in psychic costs results in a downward shift of the satisfaction function.

Finally, we note the behavior of the aware group in Study 5 replicates Study 1 in a different cultural sample (in Eastern as opposed to Western Europe). However there was a difference. Participants from Eastern Europe were more satisfied with larger choice sets as opposed to their Western counterparts, that is, the peak of satisfaction function for former lies to the right of that for the latter (compare Figures 1.2 and 1.5). The reason for this finding is not apparent and requires further investigation.

Figure 1.6A

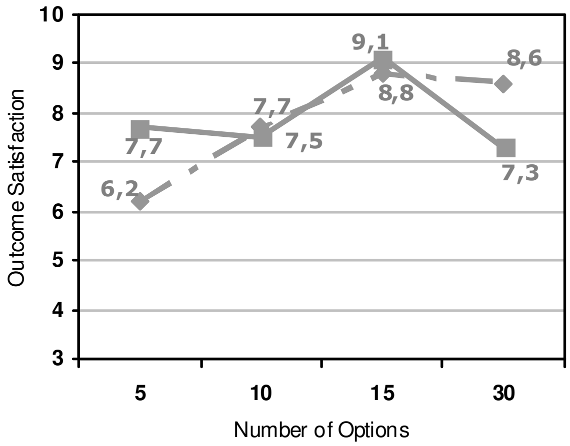

Figure 1.6B

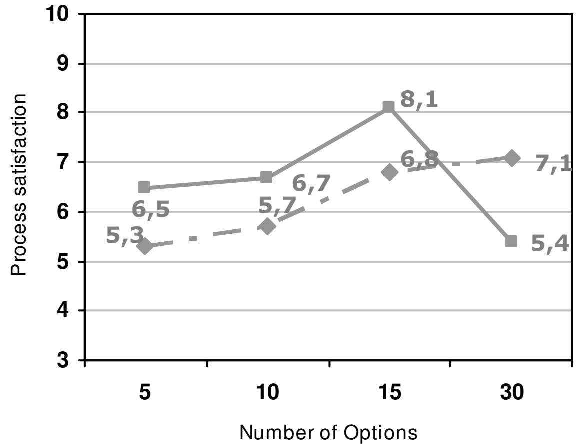

Figure 1.6C

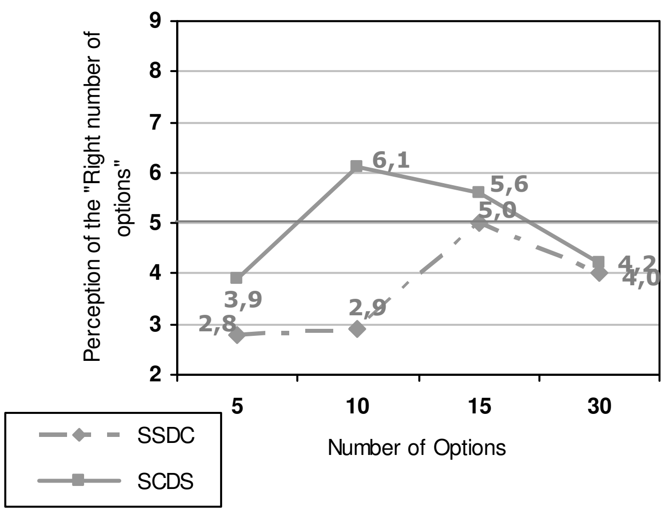

Figure 1.6: Effect of different visual presentation, Study 5. A. Outcome satisfaction; B. Process Satisfaction; C. Perception of the “right number” of options in the set.

1.8 General Discussion

This paper has explored the nature of satisfaction from choice as a function of characteristics of choice sets. Building upon the theoretical insights of Coombs and Avrunin (1977), we suggested that as the number of alternatives increases, so do the benefits and costs. However, whereas the former "satiate," the latter "escalate." The net effect is that satisfaction is an inverted U-shaped function of set size. Our studies provided support for this proposition.

At a theoretical level, our goal was to make explicit the implications of perceptions of costs and benefits of the choice process. To test our theoretical framework we manipulated differences in cognitive costs by contrasting satisfaction from choice when sets varied in color as opposed to shape. We further assessed the asymmetry for colors and shapes using behavioral and biological measures and demonstrated that alternatives differing in shapes are more taxing. As a result, and as a direct verification of our theoretical framework in a between-participants design, larger sets with alternatives differing in color were viewed as being both more satisfying and attractive than those with alternatives varying in shape. That is, the location of the peak of the satisfaction function was influenced by visual presentation of the choice set.

Costs as well as benefits of choice may also depend on individual characteristics. First, awareness of the existence of other choice sets influenced resulting satisfaction. We suggested that when other sets are salient people incur additional psychic costs which, in turn, result in a downward shift of the satisfaction function.

Second, we found that gender and culture may also affect perceptions of costs and benefits. For the choices examined here, the satisfaction curve for women lay above that for men. In addition, the peak of the curve of Eastern European participants was shifted to the right of that for Western Europeans. We had no explicit hypotheses concerning these findings but suggest that they provide a useful springboard for future research. In particular, we suspect that type of choice could moderate these kinds of individual results. Though the benefits and costs may depend on different factors, we stress again that the inverted U-shape relation between satisfaction and choice set size was replicated in different settings.

We now outline implications and suggestions for further research.

First, in our experimental tasks, participants were required to make a choice. In many situations, however, people may decide to avoid or defer choice (see, e.g., Dhar, 1997) and it is also important to predict this phenomenon. One way of thinking about this within the framework of Table 1.1 is to predict that choice is deferred or avoided when expected satisfaction is negative, that is, when perceived costs exceed benefits. For example, imagine the effect of imposing time limits on an important choice such that cognitive and psychic costs increase rapidly and the person decides to defer choice (i.e., satisfaction becomes negative). Similarly, when the perceived costs are higher than expected benefits of evaluating the entire set people may also shift to using simplifying strategies (see, e.g., Payne, Bettman, & Johnson, 1993). An advantage of our framework is that we can specify the expected effects of different variables in this process as well as predict differences due, for example, to severity of time limits or importance of the decision.

Second, we did not vary economic considerations in our experimental work. However, our framework suggests how these might affect the satisfaction function. On the one hand, there would be a desire to see more alternatives as decisions become more important. At the same time, however, important choices could induce greater psychic costs as people become more concerned about knowing their preferences and the possible regret of making errors (thereby reducing the number of alternatives they would like to see). When economic stakes are high, we would particularly expect to see expertise have a large effect on the location of the peak of the satisfaction function. Thus, for example, in choosing a pension plan, we would predict that the ideal number of alternative portfolios for a specialist (e.g., a security analyst) would far exceed that of a financial novice. More generally, we believe much could be gained by linking our framework to the literature on expertise.

Third, in our study participants were making choices for themselves. An intriguing change to the implied costs might occur if they were making choices on behalf of others, that is, as an agent. For example, if a financial specialist were selecting a portfolio for a friend as opposed to herself, would she be willing to examine more alternatives? To the extent that this would make the person feel more responsible, it follows that she probably would (see, e.g., Tetlock, 1991).

Fourth, the optimal number of alternatives (for satisfaction) in our studies was found to be 10 or 15. These numbers are exactly the same as those reported by Miller (1956) for the "channel capacity" of visual positioning, that is, the number of visual positions the human eye can distinguish without making errors. It is unclear whether this is a coincidence. However, it suggests investigating whether satisfaction is an inverted U-shaped function of the number of alternatives when these are not characterized visually but by, say, tone, taste, or odor. Building upon our theoretical framework, we would still expect satisfaction to be an inverted U-shaped function of the numbers of these stimuli. Miller (1956) argued that the "span of absolute judgment" is greater for visual stimuli than for tones or taste stimuli. Therefore, as the costs of processing the latter are higher, we would also expect the location of the peaks of the satisfaction functions for these to lie to the left of those for visual stimuli.

Fifth, in this experimental work we simplified by focusing on simple objects that differed on only one or two attributes. Clearly, an important next step will be to extend the approach adopted here to more complex products in naturally-occurring field studies.

In summary, we have presented a simple theoretical rationale that makes explicit the reasons underlying the inverted U-shaped function that describes the relation between satisfaction (both outcome and process) and the number of alternatives in a choice set. At one level, good "common sense" suggests that people will be unsatisfied and confused by having "too many" choice alternatives. Indeed, at an anecdotal level it is interesting to note that the German retail chain ALDI carries 35 times less products that its rivals – traditional supermarkets – but sells more of each product than its competitors (Kumar, 2006). Whereas it would be foolish to generalize from this specific case, it is clearly an important matter to understand when there are "too many alternatives" and how different variables contribute to the satisfaction that people experience from choice. Our goal has been to help elucidate this issue.

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Appendix 1.A: Gender effects for four dependent variables

Measure	Gender dummy		Interaction: options * gender	
	Study 1	Study 5 Unaware Group	Study 1	Study 5 Unaware Group
Satisfaction from the gift box	F(1, 115) = 4.07 p = .046	F(1, 115) = 7.16 p = .009	F(3, 112) = 0.49 p = .693	F(3, 112) = 1.55 p = .206
Satisfaction from the decision-making process	F(1, 115) = 2.37 p = .013	F(1, 115) = 7.87 p = .006	F(3, 112) = 2.27 p = .084	F(3, 112) = 0.14 p = .935
Difficulty level	F(1, 115) = 0.08 p = .775	F(1, 115) = 0.49 p = .487	F(3, 112) = 0.02 p = .997	F(3, 112) = 0.37 p = .774
Perception of the right number of options	F(1, 115) = 0.17 p = .683	F(1, 115) = 1.08 p = .302	F(3, 112) = 2.01 p = .117	F(3, 112) = 1.26 p = .290

Appendix 1.B: Complexity effects for four dependent variables

Measure	Complexity dummy		Interaction: options*complexity	
	Study 1	Study 5 Unaware Group	Study 1	Study 5 Unaware Group
Satisfaction from the gift box	F(1, 115) = 9.81 p = .002	F(1, 115) = 5.72 p = .018	F(3, 112) = 1.14 p = .337	F(3, 112) = 2.72 p = .048
Satisfaction from the decision-making process	F(1, 115) = 3.34 p = .070	F(1, 115) = 0.07 p = .791	F(3, 112) = 0.18 p = .908	F(3, 112) = 0.26 p = .853
Difficulty level	F(1, 115) = 1.23 p = 0.270	F(1, 115) = 0.02 p = 0.878	F(3, 112) = 0.09 p = .966	F(3, 112) = 1.29 p = .282
Perception of the right number of options	F(1, 115) = 0.79 p = .377	F(1, 115) = 1.03 p = .312	F(3, 112) = 0.17 p = .915	F(3, 112) = 1.37 p = .256

Chapter 2

Economic Decision Making Under Conditions of Extreme Time Pressure and Option Overload: An Eye-Tracking Study[8]

2.1 Introduction

Consider the problem of a consumer in a modern supermarket. The typical store sells more than 40,000 items and in many product categories it offers hundreds of options.[9] The typical consumer is also time-constrained and cannot afford to too much time making each selection. This situation gives rise to the two questions studied in this paper: Can consumers make good choices under extreme time pressure and option overload? Can the computational processes that they use to solve this problem be exploited by sellers in order to manipulate their choices?

We study these two questions by setting up an experimental version of the consumer's supermarket problem. Hungry subjects are presented with sets of 4, 9 or 16 familiar snack items (e.g., Snickers candy bars and Lay's chips) and are asked to make a choice within 3 seconds. Items are displayed using pictures of the actual packages of items. Besides choices and reaction times, we also record the entire process of visual search using eye-tracking.

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[8] This work was done in collaboration with Rosemarie Nagel (Univeristat Pompeu Fabra); Johannes Pulst-Korenberg, Colin Camerer, and Antonio Rangel (California Institute ofTechnology)
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[9] http://www.supermarketguur.com/page.cfm/284

With respect to the first question, we find that average choice efficiencies in all choice sets are quite large (about 80%). This is especially surprising given that the eye-tracking data shows that subjects do not look at all of the items in the 9 and 16 items choice sets, and that fixations are largely random and independent of value. Our results suggest that subjects are able to make good decisions in every day conditions (e.g., a supermarket aisle) even under conditions of options overload and extreme time pressure.

In order to understand how consumers manage this feat we open the black-box of decision making and study the computational processes used by subjects to make these types of choices. We propose a "bounded rationality" model of the computational process used to make these fast decisions and test the key assumptions of the model using the eye-tracking evidence.

The basic idea of the model is simple: subjects randomly fixate on items in order to measure their values, as long as they have time, and then choose the best item within the set that was seen. Time pressure matters because people are only able to fixate on a subset of items (in the larger choice sets) so they are not always able to find the best item in the set. The key assumptions of the model are largely supported by the eye-tracking and behavioral data.

Looking at the computational process of generating choices is unusual in neoclassical economics. Traditional economists build their models and interpret their data using the concept of revealed preference, which is silent about the actual computational processes used to make choices. This is true even in many behavioral economic models (e.g., prospect theory or quasi-hyperbolic-discounting) in which subjects are assumed to act *as-if* they were maximizing an objective function, but in which the computational process of generating the choices is not spelled out. Although this view has worked extremely well in many applications, this paper is built on the premise that there are domains, such as the problem of consumer decision making under time-pressure, in which understanding the underlying computational process is central to understanding the economics of the problem.

To see why, note that sellers spend billions of dollars trying to manipulate in-store choice. Knowledge of the algorithm that consumers use to make their fast choices is essential to be able to make predictions about the qualitative and quantitative effects of such practices as well as about their effects on consumer well-being. Detailed knowledge of the decision-making process would also allow us to make predictions about what would happen in types of choice sets different for the ones used in the experiment (e.g., what would happen to choice efficiency if there were 50 items instead of 4, 9 or 16)? More generally, understanding the process is helpful - and perhaps even necessary - for making predictions about the types of decision making situations in which the standard neoclassical assumptions (e.g., consistency with the Weak Axiom of Revealed Preference and thus with as-if utility maximization) are likely to be either approximately satisfied or badly violated.

Our experimental design allows us to directly test the possibility that decisions can be manipulated by changing the location in which items are displayed. We find that the computational process exhibits some biases that can potentially be exploited by sellers: subjects exhibit a bias to look first and more often to items that are placed in certain regions of the display, which they also end up choosing more often.

This study builds on previous literature from economics, marketing and psychology. Choice from multiple alternatives generated great interest in previous research. While the main tenet of classic economics and psychology is that choice is always beneficial, recent studies demonstrated that large sets may be demotivating, lead to worse performance and lower satisfaction than smaller sets (Iyenar & Lepper, 2000). Previous research has also shown that medium-sized sets are more satisfying and motivating for people than large or small offerings (Reutskaja & Hogarth, 2006; Shah & Wolford, 2007). However, previous studies usually allow decision-makers to use unlimited amount of time to make their choices. We emphasize, however,that many every-day situations involve decisions made under extreme time pressure and mechanisms underlying choice in such situation are not well-understood. This paper also builds on the ideas of Payne, Bettman & Johnson (1993) which, using a precursor technology to eye-tracking called MouseLab , showed that individuals who are under high cognitive strain (perhaps due to information overload), or under time pressure, shift to simpler computational models (see also Maule &. Edland, 1997; Bettman, Luce & Payne, 1998). We build our computational 'bounded rationality' model on this insight.

In economics, several groups have used eye-tracking to study the computational process used to make strategic decisions. Using MouseLab, Johnson, Camerer, Sankar & Rymon (2002) showed that the pattern of offers in bargaining experiments could be explained to a large extent by a failure to carry out full "backward induction" since in many trials subjects simply did not look ahead to future amounts. Camerer & Johnson (2004) established a related result for the case of "forward induction". Costa-Gomes, Crawford & Broseta (2001) used this same technique to measure steps of strategic thinking in normal-form games (see also Costa-Gomes, & Crawford, 2006). Using modern eye-tracking techniques, Wang, Spezio & Camerer (2008) studied strategic information transmission and found that a combination of lookup information and pupil dilation could help predict an unobservable private information state.

Several studies in marketing have used eye-tracking to study how consumers choose products from different types of displays. Russo, & Rosen (1975) started this literature by studying how subjects moved their eyes while making hypothetical choices out of 6-item text-based descriptions of cars, and arguing, much as we do in this paper, that the pattern of eye-fixations provides a window into the computational process used to make choices (see also Russo, & Leclerc,1994). Using more modern eye-tracking techniques, Van der Lans (2006) studied how subjects locate brands within a display, but the experiment included no choice. The closest study to the current paper is Chandon, Hutchinson & Young (2002) who look at the hypothetical choices of consumers facing familiar consumer products out of large choice sets without time pressure (their average reaction time is 25s). They find, like we do, that visual attention plays a critical role in choice. Several additional studies in marketing have also used eye-tracking to study which features of ads receive most attention, but they involve no real decision-making (Loshe, 1997; Maughan, Gutnikov & Stevens, 2007; Pieters, Rosbergen & Wedel, 1999; Pieters & Wedel, 2004). Some of these studies have found, as we do, that display location impacts fixations. Note, however, that none of these papers has studied real choice under time pressure and option overload. We emphasize that both the model and the eye tracking evidence that we present are new to this literature.

The paper is organized as follows. Section 2.2 describes the experimental design. Section 2.3 describes results about the performance of the choice process. Section 2.4 provides a model of the computational process generating the choice. Section 2.5 tests the key assumptions of the model using the eye-tracking data. Section 2.6 explores the qualitative and quantitative nature decision bias implicit in the model. Section 2.7 concludes.

2.2 Experimental Design

The aim of this laboratory experiment was to study economic decision-making under conditions of extreme time pressure and overload.

Forty-one Caltech undergraduates participated in the study. Individuals were excluded if they had a history of eating disorders, had dieted in the past year, were vegetarian, disliked junk food, or were pregnant. The selection criteria were designed to recruit individuals who liked junk food and were not trying to control their diet. Subjects received 35 US dollars for participating and provided informed consent prior to their participation. Participants were asked to eat and then fast for three hours prior to the experiment. No deception was used.

At the beginning of the instruction period participants were told that they will have to stay in the lab for an additional 30 minutes at the end of the experiment. During this time they were allowed to eat the food item that they chose in a randomly selected trial according to the rules described below, but no other foods or drinks were allowed. Subjects made choices out of a set of 70 popular snacks such as candy bars (e.g., Snickers Bar) and potato chips (e.g., Lay's).

Participants performed two tasks: (1) a liking-rating task, and (2) a choice task.

During the liking-rating task subjects had to answer the question "How much would you like to eat this item at the end of the experiment?" on a scale of -5 ("not at all") to 5 ("very much"), with 0 denoting indifference. The liking-rating trials started with a 1s central fixation cross, followed by a 3s presentation of a high-resolution picture of the item to be rated. Pictures were 400x300 pixels in size and showed both the package and the food. Then subjects entered their liking-rating at their own pace using the keyboard. The items were shown in random order. There was a 1s inter-trial interval with an empty screen.

During the choice tasks subjects were shown 75 choice sets consisting of either of 4, 9, or 16 snack food items (25 of each of the three sizes). The items were presented simultaneously on a computer screen (see Figure 2.1 for examples). The sets were presented in such a way that the average distance among items was equalized across set sizes. The identity and location of items was fully randomized. The order of the choice sets was also randomized. As perceived variety may be affected by the number of identical items within a set (Kahn & Wansink, 2004), we constructed sets such that no identical items were ever present in the same choice set.

Set size 4 Set size 9 Set size 16

Figure 2.1: Examples of screenshots for the set sizes 4, 9, and 16.

Before the appearance of each set, the subject was shown a black screen with a central white fixation cross. The subject had to maintain continuous fixation on the cross for two seconds before the choice set was displayed. This was enforced with an eye-tracker and it was implemented to eliminate “anticipatory fixations”.

Each choice set was presented for a maximum of 3s. Participants, however, could make their choices in less than three seconds. Two seconds into the choice period subjects heard a beep indicating that participant had exactly one second left until the choice set would vanish. Subjects indicated their choice by pressing the keyboard while fixating on an item. Prior to making actual choices, subjects went through 12 practice rounds to familiarize themselves with the procedure.

At the end of the experiment a trial was selected at random and the subjects were given the chance to eat the food that they choose in that trial. Subjects were penalized with a loss of $3 if they failed to make a choice within three seconds in the selected trial.

The entire choice process was monitored with an eye-tracker (Tobii 1750, Sweden), which recorded the positioning of the eye gazes on the screen every 20 ms with an approximate resolution of 0.25 square inches.

After the experiment subjects answered a questionnaire regarding their consumption habits of the snack food items. The experiment, including the instruction period, lasted an average of 60 minutes, including the 30 minutes that a participant had to spend in an adjacent room while eating his food.

2.3 Performance of the Choice Process

We begin the analysis of the experimental data by investigating the performance of the choice process. We are interested in two questions: Are subjects able to make good choices under conditions of time pressure? Does the quality of their choices deteriorate with the size of the choice set?

In order to measure the performance of the choice process one needs to have an *independent* measure of what is the best choice that can be made out of every budget set. Our liking ratings provide such a measure. Conceptually, the liking ratings are forecasts of the experienced utility that subjects expect to get from consuming each item. In the absence of noise, the optimal choice in any given trial is to pick the available item(s) with the highest possible liking-rating. Thus, one can think of the liking-ratings as a utility index over items.

Given this, we can define the efficiency of a choosing item i out of the set S as follows:

$$\text{Efficiency } (i|\text{S})= \frac{l(i)-l(i^{\min})}{l(i^{\max})-l(i^{\min})},$$

where i^{max} is an item in S with a maximal liking-rating, and i^{min} is an item in S with a minimal liking rating, and $l(.)$ denotes the liking-rating. Note that Efficiency=1 when a best item is chosen, and Efficiency=0 when a worse item is selected.

Is this a satisfactory measure of performance? The main question studied here is whether time pressure and overload interferes with a subject's ability to select the best alternative option. An alternative measure could have been obtained by giving subjects the same choice sets at the end of the experiment, observing which choices they would have made in the absence of any time pressure, and then comparing those choices with the ones made under time pressure. We acknowledge that, in comparison to this alternative measure, our concept of efficiency has two important shortcomings. First, it is sensitive to monotonic nonlinear transformations of the liking-rating measure. Second, it is probably measured with noise both across subjects, since they are likely to interpret the scale differently, and within subjects, as they map their "feelings" about the items to the scale.

Given this caveats, why did we chose our alternative measure of performance? First, in several previous experiments we have found that liking-ratings and "revealed preference" measures such as willingness-to-pay (elicited with an incentive compatible Becker-DeGroot-Marshak procedure) are extremely highly correlated within subjects (Armel & Rangel, 2008; Armel, Beaumel & Rangel, 2008; Plassmann, O'Doherty & Rangel, 2007). In fact, the high-efficiencies described below also suggest that the liking-ratings are good measures of the value that options are assigned during the choice process. Second, our measure can be obtained more quickly from subjects, which has experimental advantages. Third, our measure provides a natural continuous measure of efficiency, whereas the alternative described above only provides a 0-1 measure. Finally, and most importantly, qualitatively our results are robust to monotonic transformations of the liking-rating function.

In the analyses that follow we use the following measurable notions of visual attention: fixation, initial fixation, and refixation. A fixation occurs when a subject looks at an item for a continuous period of time (typically a few hundred milliseconds). Note that during a fixation subjects might look at different parts of the picture (these small eye movements within a fixation are known as microfixations). A fixation on an item is an initial fixation if that is the first time that the subject fixates on an item during a trial. If not, it is called a refixation.

2.3.1 Result 1. Choice efficiency is comparable across choice sets

Figure 2.2A shows that the average efficiency of choices is quite high and does not vary with the set size: it is 85% for N = 4 and 83% for N = 9 and 16, which are insignificantly different (lowest p = 0.24). Furthermore, if the liking-ratings are measured with noise, these efficiency measures are biased downwards.

Given the extreme time pressure, and the fact that subjects are only able to see a subset of the items during the search process (see Result 3 below), the high performance in the larger sets is quite surprising and leads to a natural question: What properties of the choice processes and situations are responsible for generating these high efficiencies? The answer to this question turns out to be rather simple ex-post. As a result of simple combinatorics, in a randomly chosen budget set the difference between the best item and the next-best items decreases with set size — in particular, large choice sets will have several options clustered near the high end of the distribution. This property is sufficient to offset the failure to see (and hence choose) the very best items in the larger choice sets. The compression of the values at the top is seen in Figure 2.2B, which shows the average difference between the value of the best item and the value of the next-best item for different set sizes. Note that the difference drops sharply with choice set size (all differences $p < 0.003$). It follows that even if people are not choosing the best item, in the 16-item sets their choice will be close to optimal if they choose the next-best item.

This combinatorial property of the choice sets is crucial because subjects are less likely to see and choose the best items from larger choice sets. For example, in the subset of cases when there is a unique best item, subjects see it 90% of the time in 4-item sets but only see it 40% of the time for 16-item sets (Figure 2.2C; all cross-set differences significant at $p < 0.001$). The corresponding probabilities of *choosing* the unique best item are about 69% and 33% (Figure 2.2D, $p < 0.001$). But if they happen to *see* the best item they choose it equally often, about 75% of the time, in all sets (Figure 2.2E, lowest $p = 0.29$). The percentage of time that the best seen item is selected is also about 75% and is similar across set sizes (Figure 2.2F). Together, the panels of Figure 2.2 show that subjects are good at choosing the best item when they see it, and choosing the best item that they have seen, but that in large sets they are less likely to choose the best item *only* because they are less likely to see it.

2.4 Model

As shown in Figure 2.2, subjects' ability to make good choices depends on their ability to see the best items in the display. For example, we have shown that, regardless of the set

Figure 2.2A

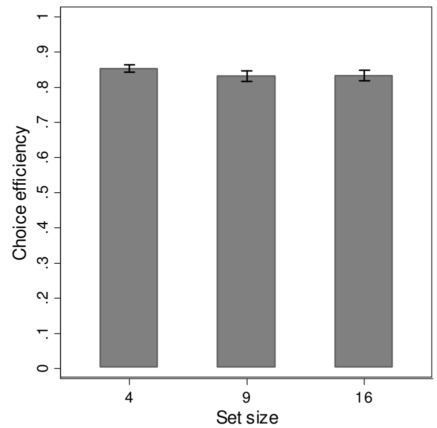


Figure 2.2B

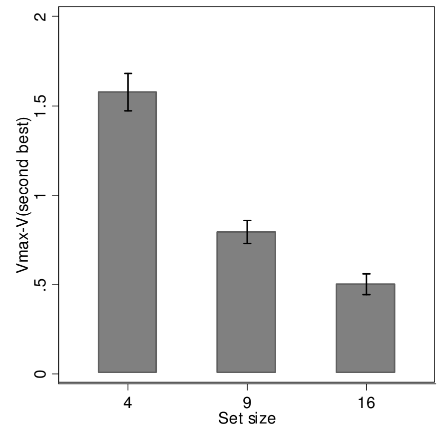


Figure 2.2C

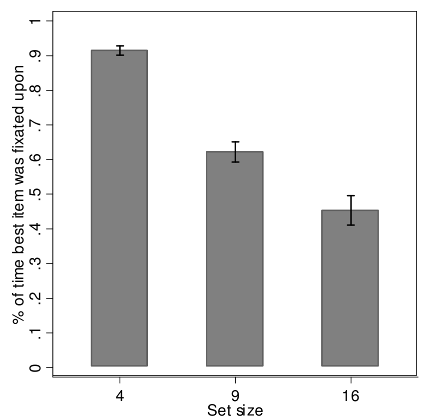


Figure 2.2D

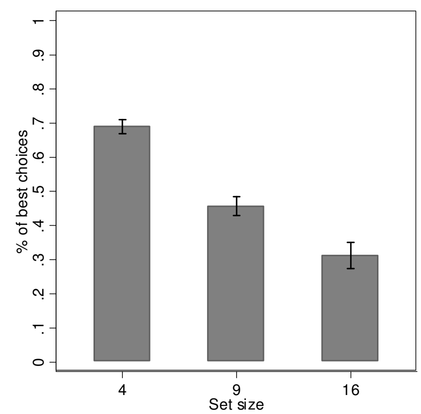


Figure 2.2E

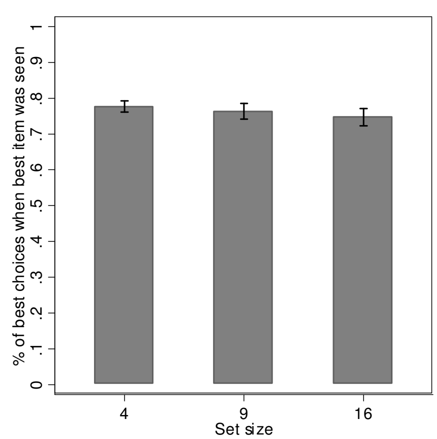


Figure 2.2F

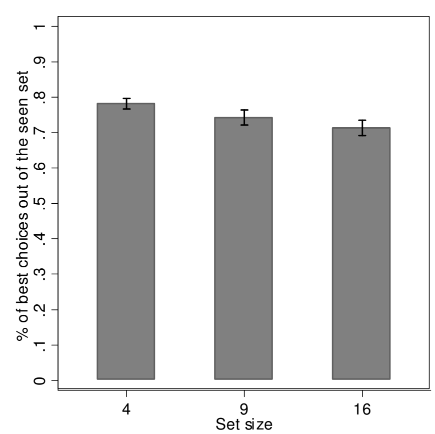


Figure 2.2: A. Choice efficiency; B. Difference in the liking-rating between the best and second best alternative in the choice set; C. Fraction of trials (with a unique best item) in which the best item was fixated upon; D. Fraction of trials (with a unique best item) in which the best item was chosen; E. Fraction of trials (with a unique best item) in which the best item was chosen *conditional on the best item being seen;* F. Fraction of trials in which the best item seen in the trial was chosen. In all of the figures error bars denote standard error measures.

size, efficiency is high when the best items are seen, but not when they are not. This raises a natural and important question: What is the computational process used by the subjects to make choices under time pressure and why do fixations play such an important role?

In this section we propose a simple model of the computational process used by the subjects that we then test in detail using a combination of eye-tracking and choice data.

Subjects search through the choice set using a sequence of distinct fixations and sequential fixations within each trial. Let F_t denote the identity of the item seen in fixation t. We assume that during each fixation t the brain computes several variables: 1) A value V_t to the item that it is looking at; 2) a cached value C_t equal to the maximum value of all items seen previously (including the current one); and 3) a label for the identity of the best item seen so far which we denote by k_t . Note that $C_t = max\ (C_{t-1},V_t)$ and so $k_t=F_t$ if $C_{t-1}<V_t$ and $k_t=k_{t-1}$ otherwise. We assume that $C_0 = V_1$.

We assume that the identity of all initial fixations is random with respect to the item's value (i.e., subjects attentional processes are not able to guide the fixation to the best items unless they have been previously seen in the trial). This does not rule out the possibility that they might be influenced by other variables such as the location in the display (see section 2.6) or by their location relative to previously seen items (in our data most eye movements are left-to-right and up-to-down and that barely any are in a diagonal direction).

At the end of every fixation the brain decides whether to stop the search process and choose the best item seen so far, with probability p_t, or continue the search by looking at a new item, with probability 1-p_t. We assume that p_t increases with the time elapsed within the trial (and thus with the fixation number) as well as with the cached value C_t.

It is straightforward to see that the number of fixations plays a crucial role in this model: on average subjects make good choices when they see a lot of items, but not when they see few items. This naturally raises the question of fixation duration. We assume that fixation duration is fixed and independent of values and set size. This assumption is based on the idea that there is a biological limitation to how fast the brain can fixate on an item and extract value and that subjects move near that threshold when making decisions under extreme time pressure.

How does the model account for the key features in Figure 2.2? Given the fixed fixation duration, the percentage of items seen decreases across choice sets. Since subjects cannot choose an item that they do not see, this implies that the probability of choosing the best items out of the entire choice set decreases with the set size. However, since there is perfect maximization within the seen set, set size does not matter *conditional on having gone through a search process that fixated on the best item.*

Note that this simple model makes several extreme simplifications that are only approximations to our data and that should be explored and relaxed further in future work.

First, we assume the cached value at every step is computed by a perfect maximization algorithm. This is probably not true given extensive evidence on biologically based "soft-maximization" and binary choice with errors (for recent reviews see Wilcox, 2008; Rangel, 2008).

Second, the value assigned to an item is assumed to be independent of the length of the fixation. This is a reasonable approximation because the items are familiar and fixation times did not vary significantly across items. Note, however, that previous work has shown that fixation times can affect valuation and choices (Armel, Beaumel & Rangel, 2008; Armel & Rangel, 2008; Karjbich, Armel & Rangel, 2008).

Third, we have assumed that there is perfect memory of which item had the highest value, as well as of the items' actual value and location. This implies that the only purpose of a refixation (going back to a previously seen item) is to select or choose a previously best seen item, but not to see it again to recall a value. This "perfect recall" assumption is unlikely to hold in more complicated choice settings and would be an especially interesting complication to study. Interestingly, the extreme time pressure feature of our experiments might actually help recall in the sense that a rapid choice time makes short-term memory more effective. It is even conceivable that an extension of the model proposed, which includes memory decay, would predict that allowing longer choice times hurts choice quality (if the bad effects of memory decay outweigh the benefits from having more time to look or deliberate).

2.5 Tests of the Model's Key Elements

The goal of this section is to use eye-tracking data to test the main assumptions of the model. The first three results test the assumed properties of the fixation process that drives the search for the best item.

2.5.1 Result 2. Fixation durations decrease slightly with set size, but are mostly constant across the search process

Figure 2.3A and Figure 2.3B show statistics on the duration of fixations. Fixations are around 320 ms for the smallest choice set (N = 4) and 260 ms for the largest choice set (N = 16). These are consistent with typical fixation times in other studies (e.g., Salvucci, & Goldberg, 2000; Wang et al., 2008). The differences in fixation duration are small in magnitude, but are highly significant across choice set sizes (for all comparisons, $p < 0.001$). The differences in fixation durations are interesting for two reasons. First, it implies that the number of seen items increases with set size, which has implications for the performance of the choice process. Second, it suggests that the amount of attention allocated to each item is adjusted endogenously (and most likely automatically and unconsciously) in response to changes in set size. This finding is consistent with a view of psychological processes in which scarce computing resources are allocated in a sensible way (Becker, 1965). Consistent with this view, Figure 2.3B also shows that the fixation durations also drop a bit around the 8th fixation for sets of 9 and 16 items. This is around the time that the beep sounds, as if people are responding to the external reminder that time is running short.

2.5.2 Result 3. The number of items seen increases with set size, but the percentage of items seen decreases with set size

The decision time constraint, together with the magnitude of the increase in set sizes and decreases in fixation times, imply that people see more items in larger sets, but overall see a smaller percentage of items in larger sets (Figures 2.4A and 2.4B; all cross-set differences are significant at $p < 0.05$ one-tailed). This implies that subjects should be less likely to find the best item in the largest choice sets, which is consistent with the results shown in Figure 2.3.

Interestingly, because of the combinatorics of large choice sets described in Section 2.3, the efficiency of the cached (highest-value) item does not decrease with set size because of the smaller percentage of items seen in larger choice sets. This fact is shown in Figure 2.4C, which plots the efficiency of the cached value (i.e. the efficiency value of the highest item seen so far) across the order of fixations.[10] As shown in the figure, the cached-efficiency starts

[10] The efficiency of an item within a choice set is defined exactly as before.

Figure 2.3A

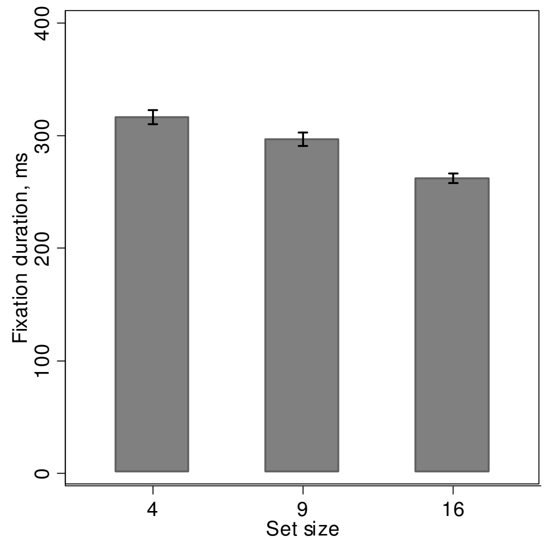


Figure 2.3B

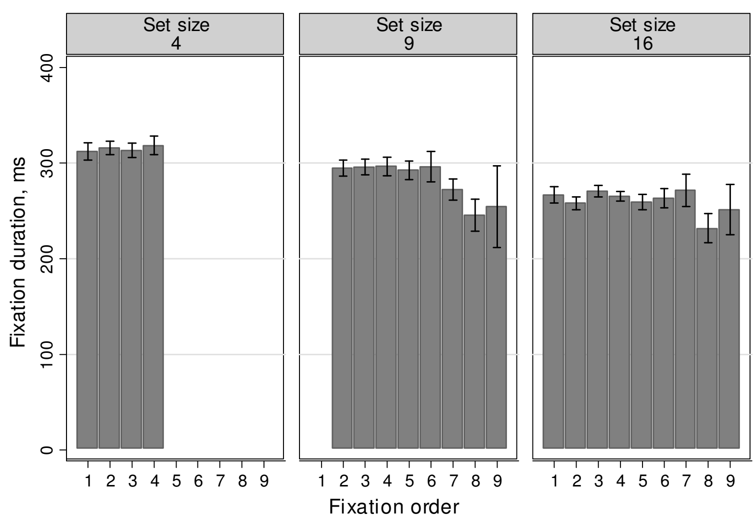


Figure 2.3: A. Average fixation duration; B. Average fixation duration as a function of fixation order.

Figure 2.4A

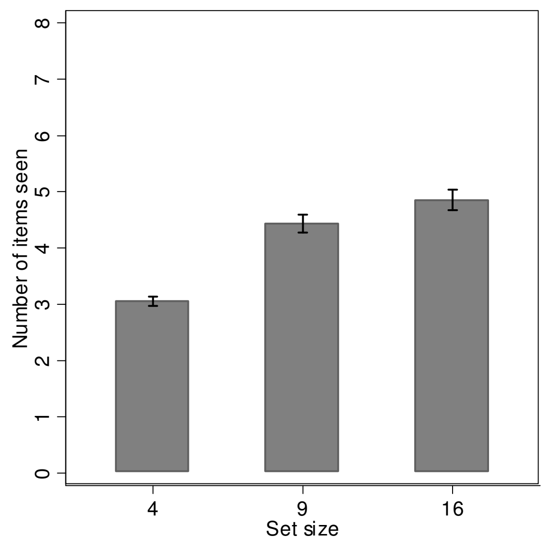


Figure 2.4B

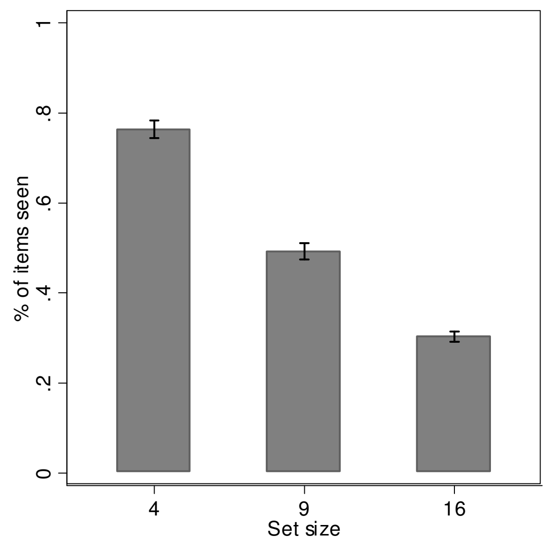


Figure 2.4C

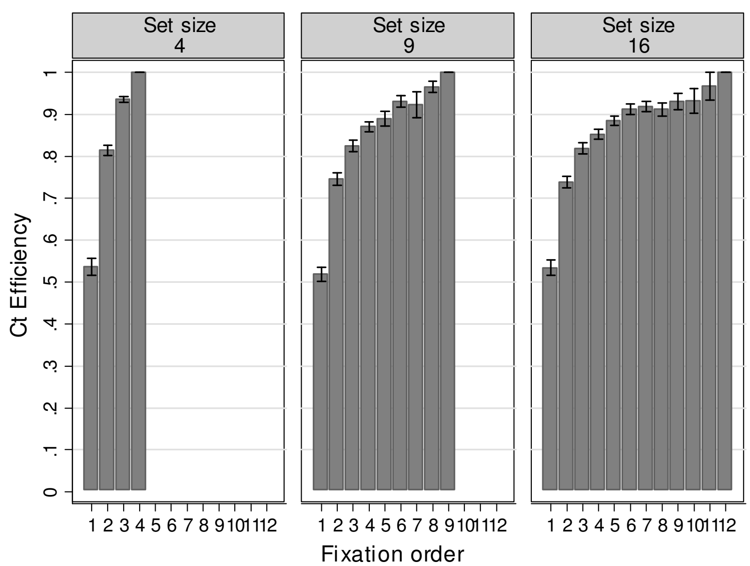


Figure 2.4: A. Number of items seen per trial; B. Percentage of items seen per trial; C. Efficiency of the cached value as a function of fixation number within the trial.

at 50%, consistent with an initial random fixation, and exceeds 90% in all choice sets by the fifth fixation.

Another important assumption of the model is that fixations are "random" with respect to value. An alternative hypothesis would have been that subjects are able to process values in peripheral vision and that this allows them to direct their fixations to items with higher relative value.[11] The following result shows that the alternative hypothesis is largely incorrect.

2.5.3 Result 4. The sequential search is mostly independent of value

Figure 2.5 shows the efficiency of items across the sequence of new fixations for different set sizes (excluding refixations to previously seen items). If people managed to always switch their attention to better and better items, there would be an increase in efficiency across fixations, but there is not. Interestingly, efficiencies are generally slightly greater than 50% (averaging 0.56, $p < 0.001$). This suggests that sequential search is mostly independent of value, although it might be the case that due to some processing in peripheral vision sufficiently undesirable items are slightly less likely to be fixated on.

Another key feature of the model, which is tested in the next result, is that the search is more likely to stop when the cached value C_t is high (controlling for time and other factors).

2.5.4 Result 5. The probability of stopping the search (and choosing) increases as C_t increases.

Figure 2.6 shows that the percentage of fixations which are the last new fixation

[11] Note that, in the alternative hypothesis, peripheral attention and direct fixations might not be perfect substitutes if the peripheral value computations can be used to guide the fixations but not to assign values to items that can be used in the process of choice.

within a trial (i.e, there may be later refixations to chose an item that was seen previously) depends on the cached value C_t. The identity of the last new fixation is important because it marks the end of the search process prior to choice. The figure shows the likelihoods of ending

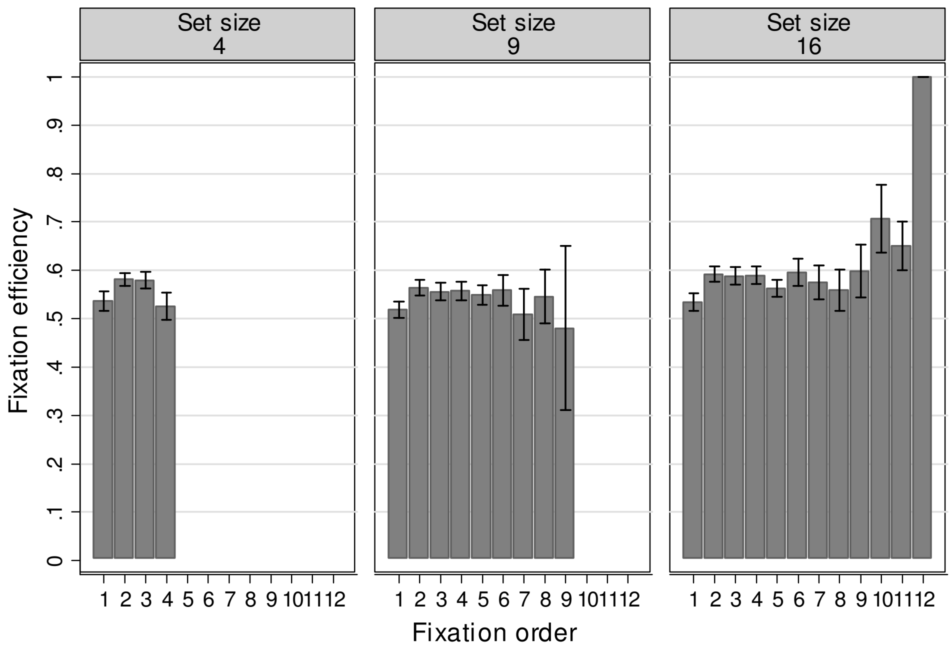


Figure 2.5: Fixation efficiency by fixation order within the trial (new fixations only, excluding refixations).

the initial search process (before refixation) as a function of the cached value during for fixations that end during the first 1500 ms ("first half of the trial"), and fixations that end during the second 1500 ms ("second half of the trial"). To explain, consider the data for set size of 4 (the left panel if Figure 2.6). In the first half of the trial (solid line) the percentage of current fixations which are the last one is around 10% when C_t is negative (i.e., in 90% of the trials they go on to look at new items). However, when the cached value is 5 (the highest possible value), about 65% of the fixations are the last new one (i.e., they are twice as likely to stop searching as they are to keep looking).

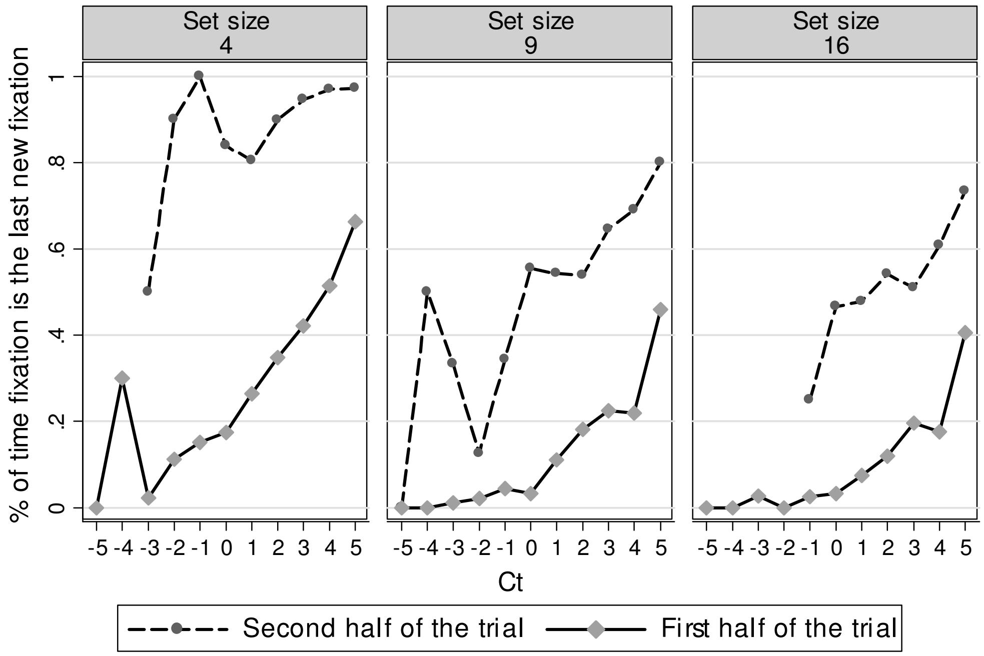


Figure 2.6: Fraction of fixations which are the last new fixation within a trial as a function of the cached value C_t. Values are presented separately for the first 1500ms (first half of the trial) and the last 1500ms (second half of the trial).

The stopping probabilities are lower for the larger choice sets, which is not surprising since subjects are able to see all four items in the N=4 case rapidly. For the first half of the trial (solid lines) the probability that a fixation is the last new one is low, but does increase with C_t. For the second half of the trial, the probability that a fixation is the last new one is much higher and highly dependent on the set size. In all cases, however, the probability of stopping the search increases as C_t increases.

A limitation of the previous analysis is that the cached value is likely to be correlated with the number of fixations, the length of time into the trial, and other variables. To address this problem we performed a logit regression of the probability that the current fixation is the last new fixation on a number of control variables (see Table 2.1). We found that after controlling for other potentially confounding variables the stopping probability is strongly increasing in the cached maximum value C_t. The analysis also shows that stopping probability is lower for the larger choice sets (as Figure 2.6 shows), is higher for the second half of the trial, is increasing in the number of fixations, and is also strongly influenced by the "beep" sound which signals one second to go in the trial.

The effect of the "beep" is interesting because it illustrates how a small change in the design of the choice process can have a large influence in behavior of economic agents with biologically driven limitations on rationality. If subjects had a perfect clock in their heads the beep would have no effect, but it does.

Another key assumption of the model is that subjects optimize within the set of items that they have seen. In particular, this implies that if the value of the last item that they see during the search (call it V_t) is better than the value of those items that they saw earlier (measured by the cached value C_{t-1}), then subjects are more likely to choose the last seen item. The following result shows that this prediction is consistent with the data.

2.5.5 Result 6. The probability that the last new seen item is chosen increases with V_t - C_{t-1}.

Figure 2.7 depicts the probability of choosing the item seen in the last new fixation as a function of V_t - C_{t-1} (the leap in value from the best of those previously-seen to the new value). The figure shows that this probability is strongly increasing in V_t - C_{t-1}, has a logistic shape, and is approximately 50% when $V_t = C_{t-1}$. This clearly shows that the subject is optimizing within each fixation between the previously best seen item and the current item. The figure also shows that these stopping probability graphs are almost identical across choice sets, which suggests that the comparison process is remarkably independent of the set size.

Table 2.1: Fixed effects logit regression. The independent variable is the probability that a given fixation is the last new fixation.

	Model 1	**Model 2**
Fixation Order	0.405***	0.389***
	(0.000)	(0.000)
Time > 1500	1.012***	1.002***
	(0.000)	(0.000)
Beep On	-	0.916**
		(0.011)
Ct	0.497***	0.498***
	(0.000)	(0.000)
Set size 9	-1.313***	-1.305***
	(0.000)	(0.000)
Set size 16	-1.609***	-1.603***
	(0.000)	(0.000)
Individual dummies included	yes	yes
Constant	-2.026***	-2.003***
	(0.000)	(0.000)
N	11,458	11,458
Log pseudo-likelihood	-4910.8	-4902.8
Pseudo R2	0.252	0.259

***, **, * denote significance at the 1%, 5%, and 10% level, respectively.
p-values are in parenthesis.
Standard errors are adjusted for clustering on subjects.
Analysis is based only on fixations prior to the first refixation.
Dependent variable =1 if fixation is the last new fixation (before the refixation start) and is =0 otherwise.
Time > 1500 =1 if the fixation ended after the trial time reached 1500 ms, =0 otherwise.
Beep On =1 if the beep was heard before the current fixation commenced, =0 otherwise.
Set size 9 =1 if the choice set size is 9; =0 otherwise.
Set size 16 =1 if the choice set size is16; =0 otherwise.

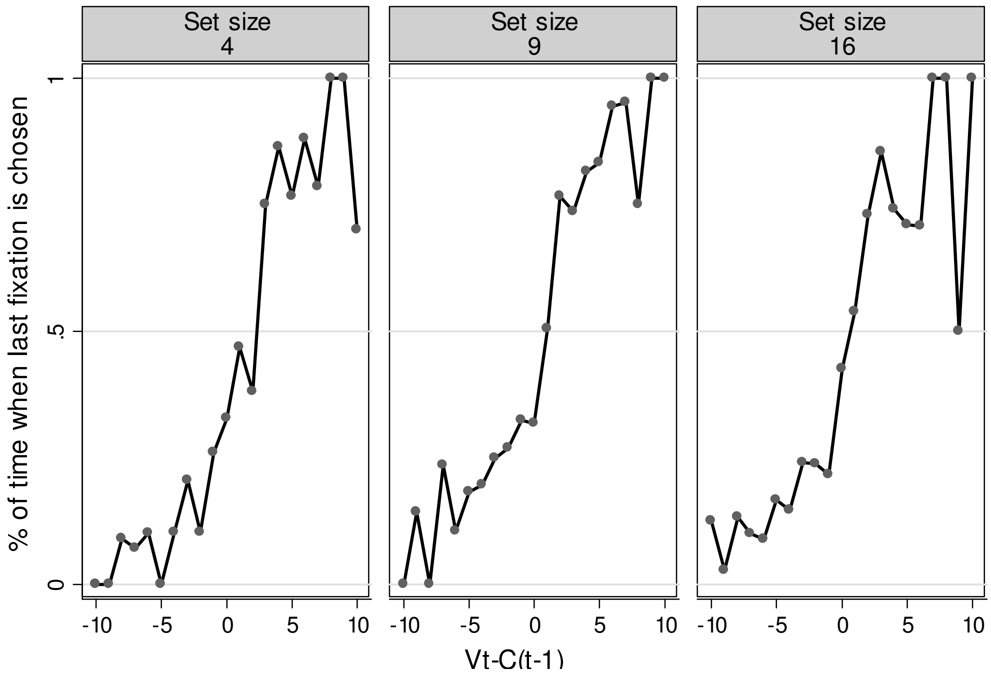


Figure 2.7: Fraction of trials in which the last new fixation is chosen as a function of V_t - C_{t-1}.

The logistic nature of the curves depicted in Figure 2.7 could result from one of two sources. First, they might be due to measurement error on the liking-ratings. Second, they could reflect true biological randomness in the choice process. Although there is mounting evidence from neuroeconomics that there is true biological randomness in the optimization process (for a review see Rangel, 2008), the methods used in this paper do not allow us to separate these two sources.

As before, a limitation of the previous analysis is that the surprise variable V_t - C_{t-1} might be correlated with the number of fixations and other factors. To address this, Table 2.2 reports the results of a logit regression of the probability of choosing the last-seen item as a function of V_t -C_{t-1} and other control variables. We found that after controlling for other potentially confounding variables the stopping probability is significantly increasing in V_t -C_{t-1}, is independent of the set size, and is an order of magnitude larger in the second half or the trial (after 1500ms).

Finally, we consider the assumption that subjects have perfect recall about the identity and value of the previously best-seen item. This assumption implies that after they decide to stop the search process, they can immediately refixate to the best item previously seen and choose it (keep in mind that choices are actually made by pressing the ENTER key during a final fixation). The next three results explore this assumption.

2.5.6 Result 7. Usually there is at most one refixation before a choice is made

According to the model, a choice is made in one of two ways: either the subject stops the search process by choosing the item seen in the last new fixation (for example, if it has the maximum possible value), or the subject stops the search process and refixates to the best previously seen item. In the first case there are no refixations. In the second case there is exactly one refixation. Figure 2.8 shows a histogram of the number of refixations that occur before a choice is made, *conditional on a refixation taking place at all*. Across all three set sizes there is a sharp spike at 1—i.e., on average, about 80% of the time there is a single refixation to the chosen item, and no further refixations.

Note that there is a right tail in the number of additional post-refixation fixations in the 16-item sets, but the effect is small. This is consistent with imperfections in working memory that are further explored in Result 9.

Table 2.2: Fixed effects logit regression. The independent variable is the probability that the items seen in the last new fixation is chosen (in which case there are no refixations).

	Model 1	**Model 2**
Fixation Order	-0.221***	-0.251***
	(0.000)	(0.000)
Time > 1500	2.344***	2.313***
	(0.000)	(0.000)
Beep On		0.248
		(0.236)
V_t-C_{t-1}	0.377***	0.377***
	(0.000)	(0.000)
Set size 9	-0.111	-0.120
	(0.435)	(0.395)
Set size 16	0.134	0.136
	(0.342)	(0.334)
Individual dummies included	yes	yes
Constant	0.285**	0.365***
	(0.035)	(0.008)
N	2904	2904
Log pseudo-likelihood	-1402.6219	-1258.6836
Pseudo R2	0.3341	0.3345

***, **, * denote significance at the 1%, 5%, and 10% level, respectively.
p-values are in parenthesis.
Standard errors are adjusted for clustering on subjects.
Analysis is based only on fixations prior to the first refixation.
Dependent variable =1 if the last new fixation is chosen, =0 if there are refixations after it.
Time > 1500 =1 if the fixation ended after the trial time reached 1500 ms, =0 otherwise.
Beep On =1 if the beep was heard before the current fixation commenced, =0 otherwise.
Set size 9 =1 if the choice set size is 9; =0 otherwise.
Set size 16 =1 if the choice set size is16; =0 otherwise.

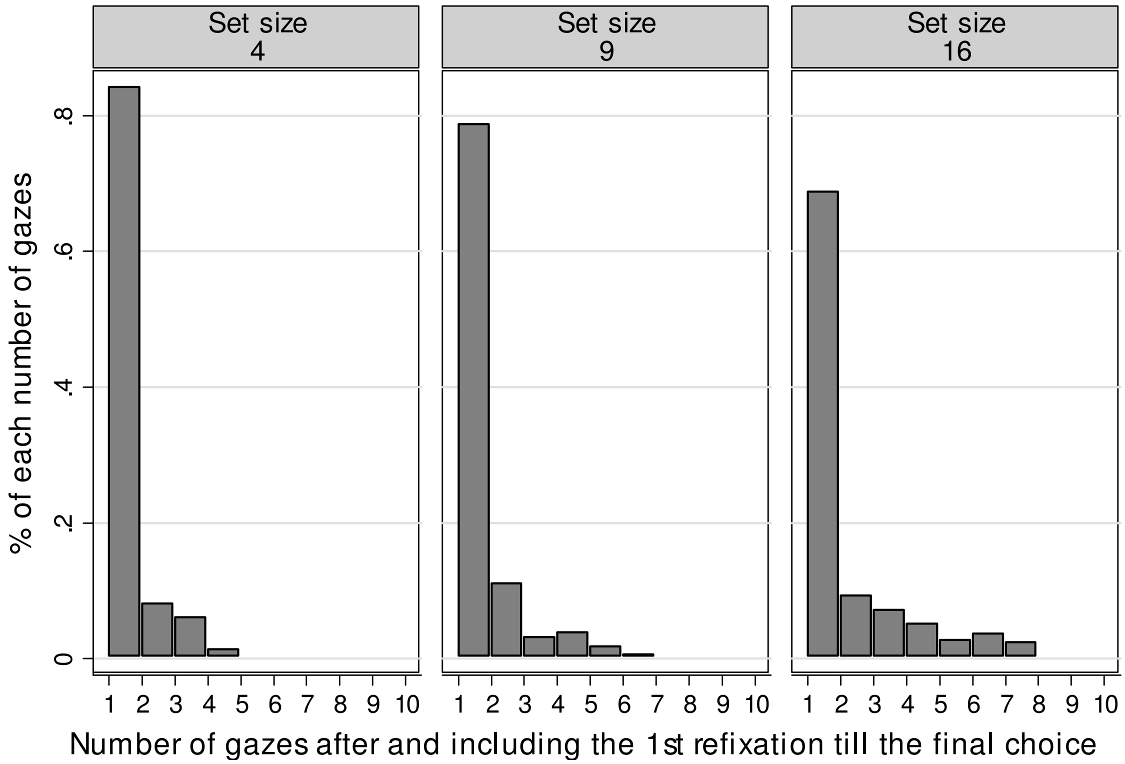


Figure 2.8: Distribution of the number of refixation of a trial (for trials with at least one refixation).

2.5.7 Result 8. The efficiencies of refixated items are high

Another assumption of the model is that when subjects refixate, they do so by looking back at the best possible items that have been seen so far. Figure 2.9 depicts the efficiencies of items that are refixated on. Note that these efficiencies are computed only over the previously seen set. Thus, if a subject refixates to the best seen item the efficiency is 100% (even if that item was not the best one in the choice set), while if he refixates to the worse seen item the efficiency is 0%. As shown in Figure 2.9, the average refixation efficiency is 77% and is quantitatively very similar across the choice set sizes. Again, this suggests that perfect recall is a good approximation, but leaves open the possibility for some imperfect working memory.

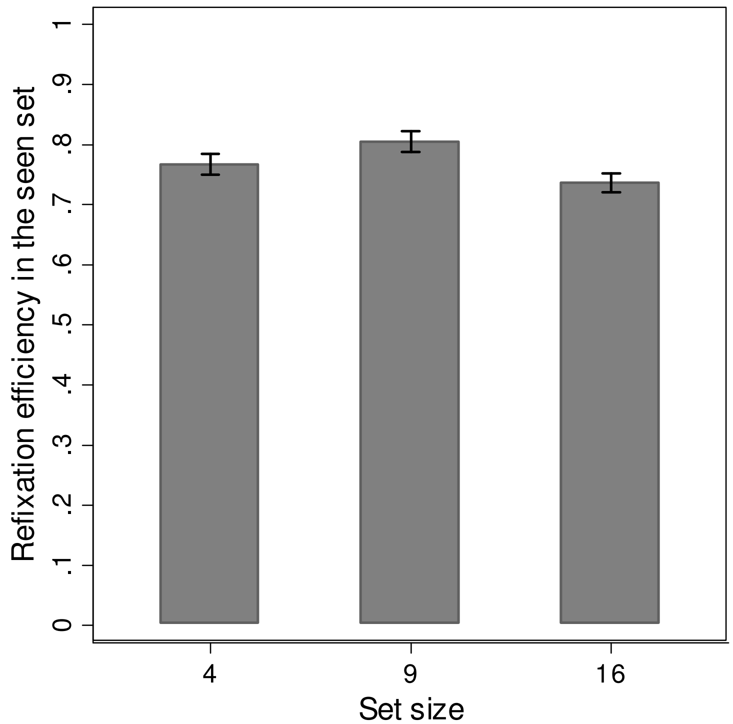


Figure 2.9: Refixation efficiency as a function of set size.

Given that the previous two results suggest that imperfect working memory might be playing a small role, we decided to perform an additional and independent test of the perfect recall assumption.

2.5.8 Result 9. There is imperfect recall about the identity of the best previously seen item.

Figure 2.10 depicts the results of two tests of the perfect recall hypothesis. The top panel shows the fraction of trials in which the first refixation is made to the best previously seen item as a function of the number of fixations that have passed since it was seen -- more than five fixations ago ("not recent") or fewer than five fixations ago ("recent"). Refixations are made to the best item about 70% of the time when it was seen recently, but that rate drops to 30% when the item was not seen recently ($p < 0.001$). The bottom panel shows the maximum efficiency of all fixations in a trial as well as the maximum efficiency of all refixations. (Here, the efficiency of a fixation or a refixation is given by the fixation of the relevant item computed with respect to the entire choice set). If there was perfect recall, these numbers would match because people would always refixate to the best item that was previously seen. This is not the case. The efficiency of the refixations is about 10% lower than the efficiency of the non-refixations ($p < 0.001$), which again is consistent with imperfect recall. Together the last three results imply that recall is good, but not perfect.

Taken together, the results in this section suggest that the model provides a reasonably good approximation of the underlying computational processes used by subjects to make decisions under time pressure.

2.6 Decision Biases

We have seen that the decision process leads to high efficiency choices on average, but that the extent to which it does so depends on the outcome of the fixation process (Figure 2.2). In particular, in large choice sets (N = 9,16), where only a subset of the items is actually seen, the quality of the choice (as measured by its efficiency) depends on the outcome of the random fixation process: it is large when high value items are seen and low otherwise. We have also seen that the fixation process is insensitive to the value of items. The model leaves open the

Figure 2.10A

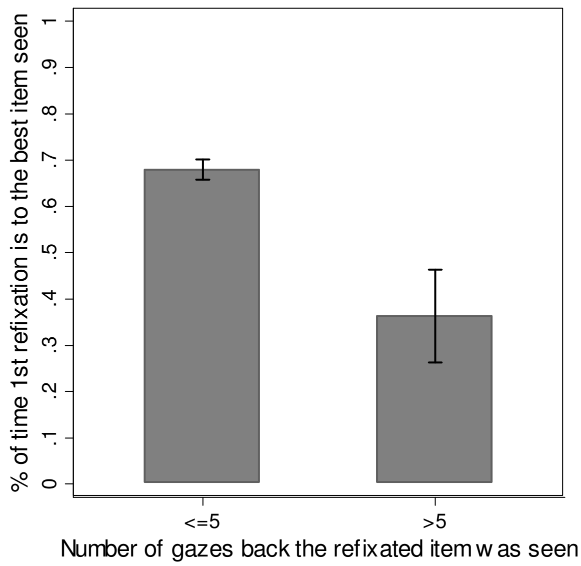


Figure 2.10B

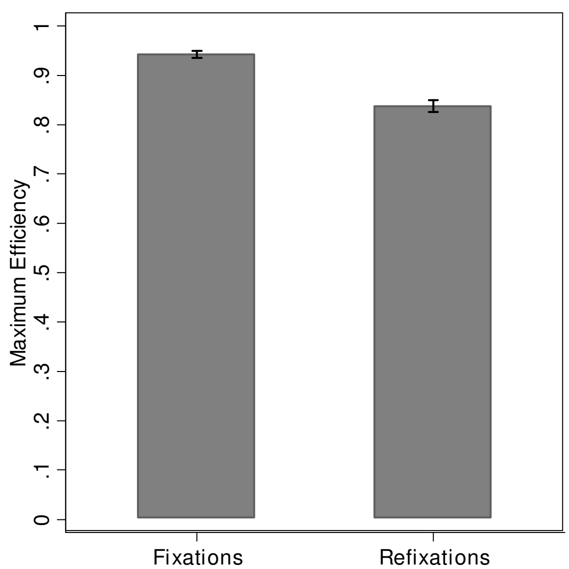


Figure 2.10: A. Fraction of trials in which the first refixation is to the best item that has been seen as a function of the number of items since it was last seen; B. Maximum fixation and refixation efficiency within a trial.

possibility, however, that the fixation process might be affected by other variables such as the location in the display. (Note that value and location are uncorrelated in our experiment since the items were randomly allocated to locations). This opens the possibility of systematic decision-making biases that, in principle, could be exploited by sellers to manipulate choices. As the following result shows, these biases exist and are quantitatively important.

2.6.1 Result 10. There are location driven biases on the initial fixation that have substantial impact on final choices

Figure 2.11 shows the initial fixations in a gray-scaled "heat map" format. The total number of initial fixations on each item is shown numerically in the locations of those items (numerical entries can take a maximum value of 25, the number of trials for each set size, and are averaged across subjects box-by-box). The lightest color is associated with the highest average of initial fixations, and the darkest color is associated with the lowest averages.

About half the initial fixations in the 4-item set are in the upper left, and 95% of the initial fixations in the larger sets are to the central item (for 9 item sets) or to the central four items (for 16 item sets). A t-test of the number of initial fixations to the most seen location versus the average of the other locations is significant at $p < 0.001$ for all set sizes.

The size of the first-fixation bias is quite large and is driven by the position of the central fixation cross on which subjects need to maintain fixation before the items appear. In the case of 9 items, the fixation cross lies exactly at the center of the middle item, which explains the extreme bias. In the case of 4 and 16 items, it lies on the middle of the screen. The subjects' first fixation is typically to the item that lies just North-West of the fixation cross.

Figure 2.11A

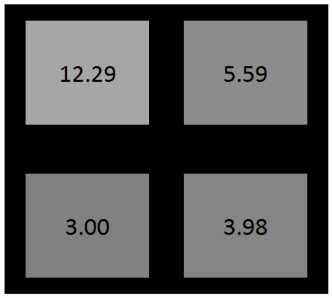
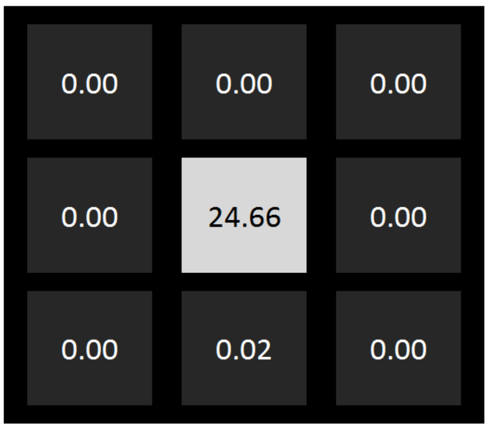


Figure 2.11B



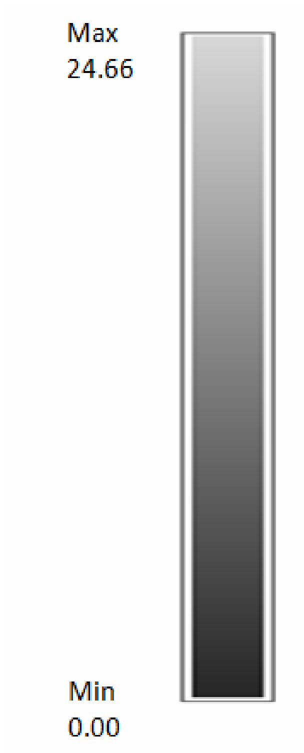


Figure 2.11C

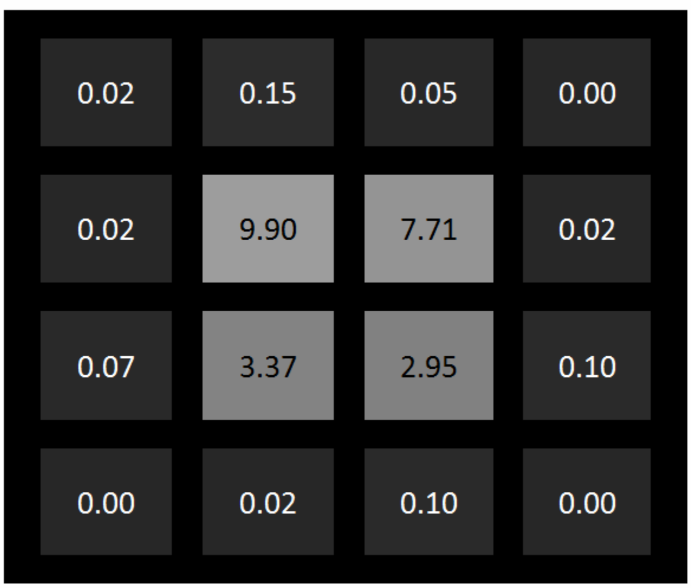


Figure 2.11: Total number of initial fixations at each display location (out of a maximum of 25 and averaged across subjects box-by-box). Analysis includes initial fixations only. Trials with only one fixation are included. Lighter cells indicate greater number of fixations. A. 4-item sets; B. 9-item sets; C. 16-item sets.

Figure 2.12 shows the same type of statistics for the total number of fixations at each location. If the initial fixation effect completely wears off these numbers should be the same in all cells for each choice set size, but they are not. About a third of the fixations are in the upper-left for N=4, and in the center item for N = 9 (compared to random base rates of 25% and 11% respectively) and almost half of them are in the center four boxes for N = 16 (base rate 25%).[12]

The combination of these initial fixation biases, and the sequential search model, imply that initial fixations should have an impact on final choices, and they do. Figure 2.13 shows the choice frequencies. There is a small tendency to choose the upper items in N = 4, and much bigger biases in the other cases (60% above average for choosing the middle in N = 9 and 25% above average for the central four boxes in the case of N = 16).[13]

Another way to measure the extent of the influence of display biases on choices is to ask what would happen if a retailer, for example, put the worst items (as judged by individual consumer ratings) in the locations at which they are likely to be seen first, or put the best items in those locations. How much would final choices vary in efficiency? Our design provides a ready answer to this question because items were randomly allocated items to locations across trials. For each subject, we weight the likelihood that they will choose an item in a particular location by their total percentage of fixations in that location, and compute the expected

[12] In the case of N=4, a t-test of the total number of fixations to the upper vs lower half of the display is significant at $p<0.001$. In the case of N=9, a t-test of the total number of fixations to the center location versus the mean of all other locations is significant at $p<0.001$. In the case of N=16, a t-test of the average total number of fixations in the middle locations versus the average of the external locations is is significant at $p<0.001$.

[13] In the case of N=4, a t-test of the total number of choices of items in the upper vs lower half of the display is significant at $p<0.051$. In the case of N=9, a t-test of the total number of choices of items displayed in the center location versus the mean of all other locations is significant at $p<0.001$. In the case of N=16, a t-test of the total number of choices made from items in the middle locations versus the mean of the external locations is significant at $p<0.001$.

Figure 2.12A

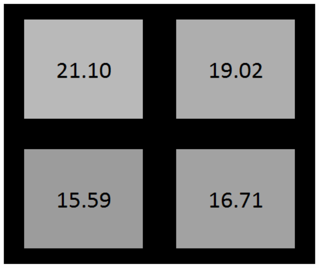


Figure 2.12B

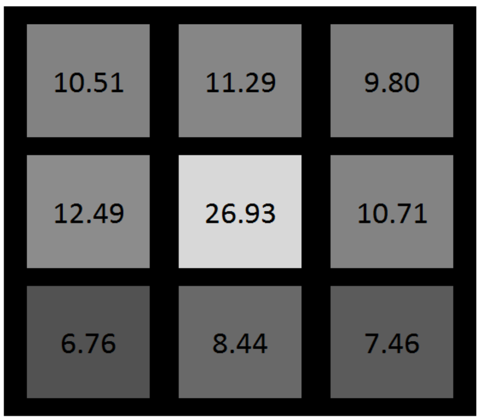


Figure 2.12C

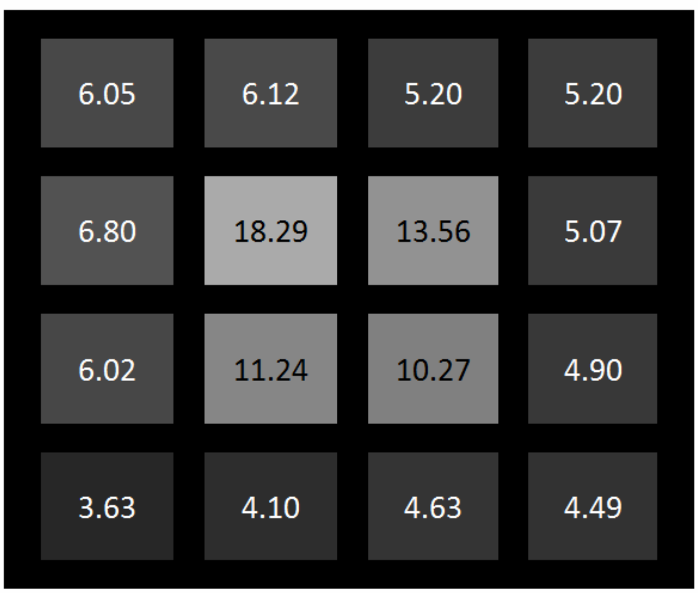


Figure 2.12: Total number of fixations at each display location (averaged across subjects box-by-box). Note that the maximum can exceed 25 since individuals might refixate in a location. Analysis includes both fixations and refixations. The last gazes are not included into the calculation of the total number of gazes. Lighter cells indicate greater number of fixations. A. 4-item sets; B. 9-item sets; C. 16-item sets.

efficiency for the configurations of items they actually saw. We then create quartiles of "good displays" (in which the best items, as they judge them, are in the locations they tended to look at most often) and "bad displays" (in which the worst items are where they looked most often). The efficiencies in these quartiles are then averaged across subjects. Figure 2.14 shows the results. When the best items are in the visual "sweet spots" the efficiency is 95%-- they are almost sure to make the best choice. When the worst items are in the sweet spots efficiency is only 65%, which is significantly better than chance choosing (50%) but not by much ($p < 0.01$ for all pairwise comparisons).

The results in this section clearly show that the choice process used by subjects when making decisions under time pressure could be potentially manipulated by interested sellers. In the real world, this could be achieved by picking special locations in displays and supermarket aisles, or by changing the packaging (e.g., by manipulating shape, size and color) in a way that attracts first fixations through their impact in bottom-up and value-independent visual attention mechanisms (Itti & Koch, 2001).

2.7 Discussion

The results in this paper provide novel insights into the economic problem of a consumer who needs to make choices from small or large choice sets under time pressure. The paper poses and addresses two main questions regarding the quality of decisions in this domain. First, we have shown that consumers can make good choices even under extreme time pressure and with option overload (when they do not have time to look at every item). An understanding of the computational processes that consumers use to make the choices provides

Figure 2.13A

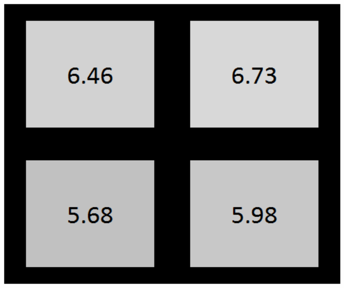
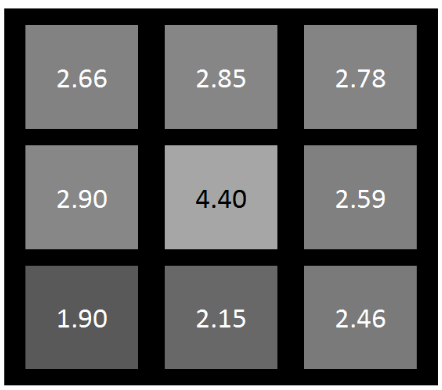


Figure 2.13B



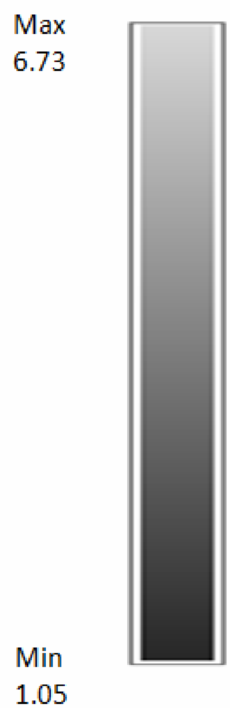


Figure 2.13C

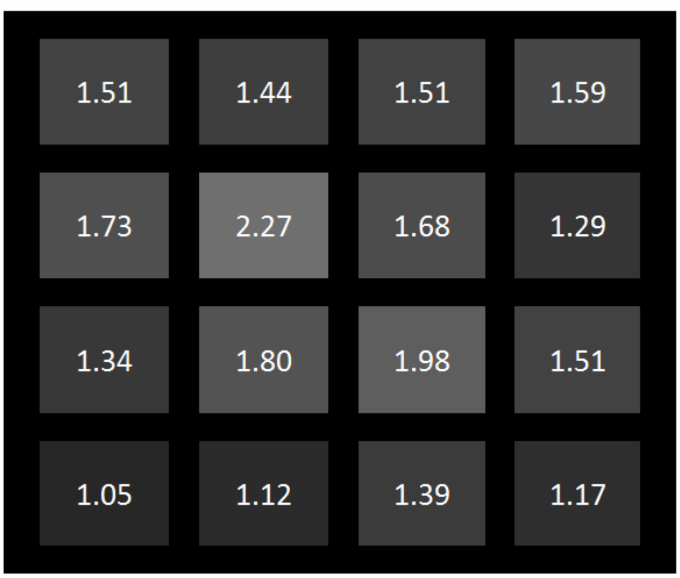


Figure 2.13: Total number of times the item displayed at each location was chosen (averaged across subjects box-by-box). Lighter cells indicate greater number of fixations. A. 4-item sets; B. 9-item sets; C. 16-item sets.

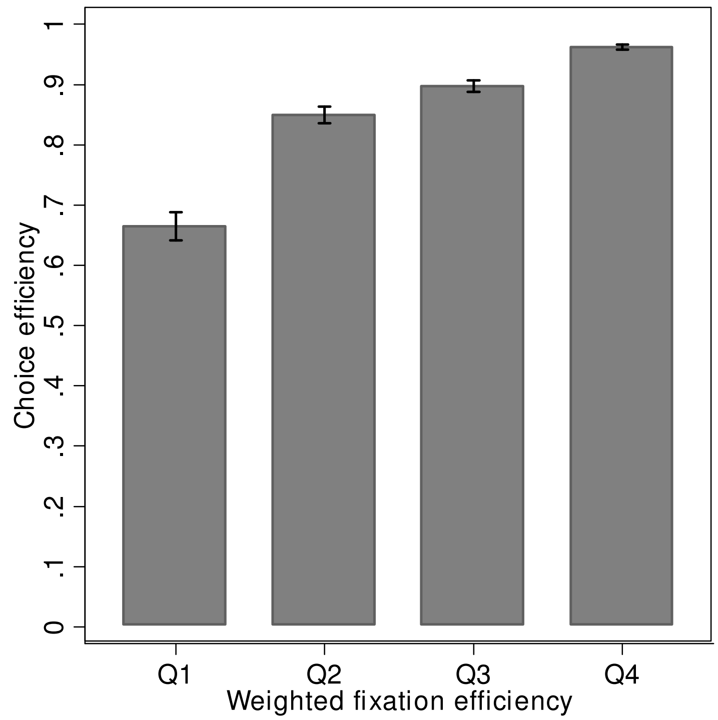


Figure 2.14: Choice efficiency as a function of weighted fixation efficiency (by quartile).

an insight for why this is the case. In small choice sets (N = 4) subjects are able to see most of the items and choose the best one about 80% of the time. In contrast, in large choice sets (N = 9,16) subjects are only able to see a small fraction of the items and thus are able to choose the best one only about half as frequently. It follows that the performance of the computational process used to make choices deteriorates as the number of options increases. However, combinatorics come to the rescue: in larger choice sets there are many alternatives close to the best one which are seen and chosen with high-frequency. This is the key reason why performance (as measured by average efficiency) does not deteriorate with set size.

Second, we have seen that choices are heavily influenced by the outcome of the fixations, and that these fixations can be affected by variables such as display location, that are not correlated with values. We have also shown that this feature of the choice process could potentially be exploited by sellers through a clever selection of packaging and in-store displays. We have also shown that these effects are quantitatively large. For example: in the case of N=9 an item in the center of the display was almost 60% more likely to be selected than similar items displayed in other locations.

These two regularities are consistent with a simple model of sequential search with perfect recall in which search is value-independent (subjects cannot deliberately guide their visual attention to high-value items) but is also display-dependent (they look first at the center and upper-left). To economists, the sequential search model might seem so natural as to be obvious. However, many studies of visual attention suggest a surprisingly different model of *parallel* search. Parallel search is implied by hundreds of experimental studies showing a phenomenon called the "pop-out effect" (Treisman, 1985). In these studies subjects are instructed to search for a particular item in a set (e.g., "Is there a T in the set of letters?"). Empirically, when items are visually distinctive in terms of easily-processed features that are noticed "pre-attentively" (e., choosing an X from a set of X's and O's), the time taken for a correct response is completely invariant to the number of items N. The fact that response times are invariant to the set size N suggests that people are looking at all of the items simultaneously (searching in parallel). If searching for the best item in a choice set exhibits a similar pop out effect, time-constrained subjects will always choose the best items even in large choice sets, and display locations will not matter. Both of our central findings are the opposite of these predictions, which implies that search is clearly not parallel as shown in many earlier studies. Our point here is simply that the sequential search model is not the only conceivable model of visual search for choice, so establishing that model as a sensible one is not simply confirming the obvious.

A comparison with previous research illustrates some differences between choice with and without time pressure. Karjbich et al. (2008) have studied decision-making using eye-tracking from sets of binary options using a similar set of stimuli. They find that subjects often make repeated fixations to the same item before making a choice, and their fixations are almost 80% longer than the ones in this paper. One potential explanation for the difference with our results is that longer fixations are useful to improve the estimates of value. This is consistent with the findings of Armel et al (2008) and Armel & Rangel (2008). Similarly, repeated fixations might be useful to improve the comparison of values. If this is correct, the brain might compute noisier estimates of value (due to the shorter fixations) and might make more errors when comparing items, when making decisions under time pressure.

One natural question for future research is how well does the model and biases that we have identified extend to other decision-making situations. We hypothesize that similar computational processes might be used by consumers in situations without time pressure in which they are overwhelmed by a large amount of information. A typical example would be the selection of an investment portfolio out of the long list of options offered by the typical investment company. Consumers might only end up considering a fraction of these options, and “marketing” factors such as location in display, color, and font-size and style might affect which ones are actually considered.

Another important question for future research is the extent to which consumers can defend themselves from the biases identified here. Our hypothesis is that this might be possible, but that it might require costly training before the choice situation, and costly deployment of attentional control at the time of decision-making. For example, consumers might have to train themselves to look at random locations in displays and to ignore certain features of packaging such as color. Furthermore, deploying such rules might be hard in practice since they require overruling powerful bottom-up attentional mechanisms (Itti & Koch, 2001).

Our findings are related to the "choice overload" literature in psychology which showed that large sets could be demotivating and dissatisfying for the consumers (Iyengar & Lepper, 2000; Iyengar, Huberman & Jiang, 2004; Reutskaja & Hogarth, 2006). Interestingly, these effects are normally studied in no-time-pressure conditions in which subjects can take as long as they want to make a choice. The typical explanation given to these results is that large choice sets and unfamiliarity leads to doubts about the quality of the choice to which people react by deferring or avoiding making a choice at all (also, see Dhar, 1997). In contrast to these findings, we forced individuals to make a decision in every trial, which rules out the postponement of choice.

More generally, we hope that this paper illustrates the value for economists trying to understand the actual computational processes that individuals use to make different types of decisions. As described in the introduction, this approach has already generated important insights in behavioral game-theory but it has not been as widely applied in economics to individual decision-making process. The recent maturing of new technologies such as eye-tracking and functional magnetic resonance imaging (fMRI) has made the development and testing of these types of models feasible and relatively low cost.

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Chapter 3

Neural Signatures of Choice-Overload and Choice Set-Value in the Human Brain[14]

3.1 Introduction

A main tenet of classic economic theory is that more choice is always desirable. However, contrary to this proposition, empirical evidence suggests that people often prefer to choose from small as opposed to large sets of alternatives. There is a growing body of research suggesting that extensive choice may be costly and demotivating (Shafir, Simonson, & Tversky, 1993; Dhar 1997; Loewenstein, 2000; Schwartz, 2000; Iyengar & Lepper, 2000; Iyengar, Huberman, & Jiang, 2004; Iyengar, Wells, & Schwartz, 2006; Reutskaja & Hogarth, 2006; Shah & Wolford, 2007).

However, in spite of great interest in the problem of choice overload, there are at least two gaps in the previous literature that we aim to fill. First, previous behavioral research focused mostly on outcomes of choice behavior (e.g., number of choices made, quality of decisions, etc.). Very few sources study processes underlying choice overload phenomena (e.g., Iyengar & Lepper, 2000; Reutskaja & Hogarth, 2006; Reutskaja et al., 2008). This occurs mainly because of the difficulty in measuring "behavioral processes". Measures that

[14] This work was done in collaboration with Rosemarie Nagel (Univeristat Pompeu Fabra); Colin Camerer, and Richard A. Andersen (California Institute of Technology), and Axel Lindner (Hertie Institute for Clinical Brain Research). Financial support from HFSP (to Rosemarie Nagel and Colin F. Camerer), and the Spanish Ministry of Education (to Rosemarie Nagel, SEJ2005-08391), and the Barcelona CREA program (Rosemarie Nagel) is gratefully acknowledged.

intend to explore the processes of choice usually rely on self-reports which can have considerable drawbacks (e.g., subjectivity, limited memory of subjects, etc.). On the other hand, biological measures that are collected via eye-tracking and brain-imaging techniques can help to uncover the processes underlying choice behavior and inform predictions of human decision making. To shed light on the mechanisms driving choice behavior, we used functional magnetic resonance imaging (fMRI) to measure participants´ brain activity when they were making choices from different-sized sets.

Second, in spite of great attention paid to the choice overload problem in behavioral, economics and marketing research the neural bases of this phenomenon are still unknown. Several sources report how primate and human brain activity is modulated by different numbers of items. Tasks used in these studies involved both the simple presentation of different numbers of items and choice from different sized sets (e.g., Nieder, Freedman, & Miller, 2002; Mash et al., 2007; Churchland, Kiani, & Shadlen, 2008). However, it is worth noting that the number of items subjects are exposed to in these studies is rather limited, i.e., typically from 2 to 5 items. How brain activity is modulated by large numbers of alternatives (e.g., more than 20) has not yet been studied.

The aim of this paper is to investigate the neural correlates of choice behavior when people are exposed to multiple alternatives. Specifically, we explore the neural processes underlying choice overload phenomena by studying the brain activity of 19 subjects who face choice from limited (6), medium (12) and large (24) sets of landscape photographs and receive one of the chosen pictures printed on a product of their choice. We explore both the physical reaction of people to the increase of the choice set size and the neural representations of "subjective" choice experience. The physical reaction is influenced by the actual number of choice items in the set and is independent of the perceptions of subjects. Subjective set value, on the other hand, is affected by participants´ subjective choice experience rather than by actual number of items.

We find that while activity in some brain areas [such as the middle occipital gyrus (MOG), lingual gyrus (LG), inferior occipital gyrus (IOG), dorsal premotor cortex (PMd), and supplementary motor area (SMA)] increases linearly with the number of alternatives, activity in other brain regions [such as the nucleus accumbens (NA), caudate, anterior cingulate cortex (ACC), medial frontal gyrus (MFG), and posterior orbitofrontal cortex (POG)] follows an inverted-U-pattern with the increase of the choice set size. Most likely, the former activity resembles the costs one incurs when choosing from different sized sets, while the later activity represents "motivation" for choosing. These data are consistent with the behavioral findings, which show that people buy more when confronted with medium-sized than small or large sets, i.e., medium-sized sets are more "motivating" (Shah & Wolford, 2007). Our study provides first evidence of the neural bases of choice overload in the brain.

Moreover, we find that brain activity is modulated not only by the actual number of choice items present in the choice set, but also by the subjective choice experience of participants. Similar to findings from previous behavioral studies (Reutskaja & Hogarth, 2006), participants generally considered that medium choice sets were of "optimal" size, while they rated smaller sets as having too few items and the larger sets as having too many. Activity in the superior parietal lobule (SPL) was correlated with such subjective value of the choice set. This pattern of fMRI-activity provides the first insight into how the brain combines the quality of choices from a set with the difficulty of making these choices into a signal that can be interpreted as the value of a choice set.

Choice experience and behavior were further shown to be affected by the amount of control or freedom people have over their decision and by the availability of an "ideal" item in the set (see Botti & Iyengar, 2006; Chernev, 2003). In our experiment, we manipulate these two important variables and explore the neural activity associated with this manipulation. Our results suggest that both "freedom" of choice and availability of a strongly preferred item modulate neural representations of choice from multiple alternatives.

We emphasize that knowledge of the processes underlying choice overload behavior is a powerful tool that can provide hints to theorists and practitioners on how to optimize choice assortments for consumers. Understanding how consumers' minds decide what is "enough" should help design marketing policies which are beneficial both for consumers and retailers (e.g. developing choice sets which include large variety without hurting consumers´ choice performance and shopping experience).

The paper is organized as follows. First, we start by examining the existing literature in the fields of both behavioral research and neuroscience that is relevant for the choice overload phenomena. Afterwards, we present the experimental design. Then we report the main findings of our study and conclude by discussing the results and their implications.

3.2 Theoretical Framework

Whereas classical economics and psychology argue that choice is always beneficial, a number of recent studies suggest that it is not always the case, and large choice offerings may lead to choice paralysis. Iyengar and Lepper (2000) demonstrated that large assortments can be demotivating. In their field study, although customers were more attracted to an array with 24 as opposed to six different jams, they purchased less from the larger than from smaller set. In addition, other studies by these researchers showed that people consume more and even perform better on intellectual tasks (writing essays) when facing limited rather than extensive sets of options. Moreover, increasing the number of alternatives in the choice set or having items with similar attractiveness may make people defer choice or simply choose a default option (Shafir et al., 1993; Dhar, 1997).

Furthermore, having many choice alternatives affects not only people´s behavior, but also their feelings and subjective perceptions of choice. The perceived difficulty of choice, for example, increases with the number of items in the choice set (Iyengar & Lepper, 2000; Reutskaja & Hogarth, 2006). People also experience post-choice discomfort, especially when the choice set is large. For example, people may feel "attached" to forgone alternatives and, therefore, experience "loss" of non-chosen items (Carmon, Wertenbroch, & Zeelenberg, 2003). Self-reported satisfaction with both the outcome and process of choosing is also affected by the number of items in the set (Reutskaja & Hogarth, 2006).

There is, therefore, a limit to how much choice is good or "enough". However, what are the processes that underlie choice and determine the optimal choice set size? Reutskaja and Hogarth (2006) propose a theoretical model that describes processes which underlie choice behavior from different sized sets. They suggest that choice has both benefits and costs which increase with the number of items in the set. However, with the number of choice options the benefits increase at a decreasing rate, i.e., "benefits satiate", while the costs increase at an increasing rate, i.e., "costs escalate". Satisfaction both with the chosen alternative and the process of choosing as well as motivation for choosing should be the sum of these costs and benefits. When the choice set is small, the benefits of choice outweigh the costs, but when choice set becomes large, the reverse happens. Therefore, satisfaction as well as motivation for choosing should be an inverted-U shape function of the number of alternatives in the choice set. The empirical evidence suggests that it is indeed the case, and both satisfaction and purchasing behavior have been shown to follow the inverted-U pattern with the number of alternatives (Reutskaja & Hogarth, 2006; Shah & Wolford, 2007).

In another study Reutskaja et al. (2008) explored the processes of visual search when people chose a snack out of different-sized sets under extreme time pressure of three seconds. Using eye-tracking techniques it was found that subjects fixate on items randomly and sequentially, measure their values, and choose the item with the maximal value seen. Overall, this strategy allows subjects to make highly efficient decisions even within an extremely short time period.

However, the mechanisms underlying choice behavior under the conditions of overload are far from being well-understood. And in spite of the great importance of choice overload problem for both consumers and producers, nothing is yet known about the neural correlates of choice behavior. Knowing how the brain processes choices from different numbers of alternatives is important as it can provide insights into the choice overload phenomenon and inform predictions of human decision-making. So, how are choices from multiple alternatives represented in the brain?

A large number of brain-imaging studies have explored the neural bases of choice behavior with limited numbers of options. Typical tasks in these studies are choosing between two actions to make (e.g., decisions in perceptual-motion tasks) or selecting between two objects or gambles (e.g., with different magnitudes of possible gains and losses, probabilities, etc.).

Only few studies have attempted to explore choice behavior from sets which include more than two choice options. A study by Churchland et al. (2008) addresses the question of how monkeys respond to 2- as opposed to 4-choice decision tasks (direction-discrimination task). The results suggest that subjects accumulate the evidence for and against the choice. At the beginning of the decision process, the firing rate in the superior colliculus was lower in the four- than in the two-option case which caused a higher threshold for termination of the former decisions.

Marsh et al. (2007) studied how human brain activity is modulated by the number of available options and expected reward. They found that the increase in the number of choice alternatives was positively associated with activation in the following brain regions: the cingulated gyrus (dACC/dmFC), precentral gyrus, medial frontal gyrus (MFG), caudate/thalamus, precuneus, and middle occipital gyrus (MOG). As the number of options increased the blood-oxygen-level dependent (BOLD) activation in these regions also increased. The authors argue that with the increase of the number of items in the set, the response conflict increased (as the competition among the options went up) and was accompanied by the linear increase in the fMRI signal in those regions. However, the number of response options that the authors studied was rather limited -- 2, 3 and 4 alternatives.

To date, no brain-imaging study has examined choices from large sets of items (e.g., sets that contain more than 20 items). However, the fact is that many every-day decisions involve choices from extensive numbers of alternatives, e.g. think of selecting a yogurt from a shelf in a well-stocked supermarket or a meal from a large menu in a nice restaurant.

The purpose of this paper is to understand the neural bases of decision-making when humans are confronted with sets of different sizes, involving small, medium and large numbers of choice options. We do not aim to study how brain activity is modulated by the selection of a particular object (and reward associated with this object), nor by how the goal was acquired, nor by how humans make decisions from limited sets. These tasks have been successfully studied in previous literature. Instead, we aim to explore how the value of the *entire set* is represented in the human brain, and how this representation is affected by the number of choice items, choice “freedom” and the availability of a strongly preferred alternative in a set.

Previous behavioral studies demonstrate that people often make more choices and experience greater satisfaction when choosing from intermediate numbers of items as opposed to small or large sets of alternatives. Therefore, we first expect to see the set size representation in the areas that were associated with reward and value in choice tasks in previous literature. These are the striatum, orbitofrontal, cingulate and parietal cortex (Platt & Glimcher1999; O’Doherty, 2004; Williams et al., 2004; Marsh et al., 2007; Plassmann et al., 2008). Some of these areas relate to representation of the value of single items or actions. However, it is not clear yet whether these areas also represent the value of an entire set, i.e., not only the value of a single item but the integrated value of the set consisting of many separate options.

Second, one brain area may be of special interest for our task, namely the anterior cingulate cortex (ACC). Previous literature suggests that apart from being associated with functions such as error monitoring or reward, the ACC might be an area that represents the “net” value of an action, which is based on accumulated evidence and cost-benefit analysis (Kennerley et al., 2006; Rushworth et al., 2007; Rushworth & Behrens, 2008). In their work Rushworth & Behrens (2008) argue that:

> “…it is possible that the ACC represents the integrated value of a course of action to reflect both the action’s intrinsic costs and benefits” (p.395), and “…ACC activity preceding a decision encodes the integrated value of an action, whether in terms of immediate gains and costs or in terms of information to aid future decision making. On the observation of an outcome, ACC activity encodes the degree to which the resulting information should influence future decisions.” (p.396)

If choice satisfaction and behavior is a sum of costs and benefits (as proposed by Reutskaja & Hogarth, 2006), and the ACC is the area that is associated with the integrated value of a course of action, then we would especially expect the activity in the ACC to follow an inverted-U pattern as the number of choice option increases. Interestingly, Marsh et al. (2007) found that activity in the dorsal ACC (dACC) increased linearly with the number of choice items. However, their choice sets were not extensive and contained at most four alternatives. We suggest that when the choice set size becomes large enough, the cost of choice may overweigh its benefits, and the activity in the dACC should level off.

In addition, the amount of choice considered "enough" may be affected by other variables, for example, by choice set presentation and "freedom" of choice. Previous research suggests that availability of a highly-preferred item in a large choice set can simplify choice (Chernev, 2003). In this paper we also examine how the presence of a strongly preferred item in the set influences participants' choices and brain activity associated with their decisions. We expect activity in areas associated with reward and value processing to be greater when people face choice sets with a strongly preferred item compared to the case when such an alternative is absent.

The literature further suggests that when choice becomes difficult, people can prefer to defer the choice or "choose not to choose" (Dhar, 1997). In our experiment we investigate the neural bases of human decision-making when participants face "free" (i.e., decide what to pick by themselves) as opposed to "forced" choices (i.e., when the item is selected for the participants). More specifically, we would expect to see different patterns of brain activity for free and forced choice conditions in areas which are associated with reward and value processing (see above). While medium sized sets should be more "rewarding" than small or large sets when participants face "free" choices, large sets might be more "rewarding" than small sets when the item is chosen for the participant (i.e., due to increased difficulty in the larger as opposed to smaller sets one may prefer the choice to be made for him/her).

3.3 Experiment

Method. The aim of our study was to investigate the neural bases of human decision making when people are confronted with limited, intermediate and extensive choice offerings. In our functional magnetic resonance imaging (fMRI) experiment subjects faced different-sized choice sets of landscape photographs from which they had to choose their most preferred one. One of these choices was then used to produce a consumer product with an imprint of the respective photograph. Participants' brain activity and eye-movements were recorded while they examined the sets and made their choices. To control for choice involvement we, first, let participants freely select the product on which the landscape picture would be printed. Subjects could choose one of the following products: mug, mouse pad, T-shirt, desk organizer, bag, or apron. At the end of the experiment a customized product with a selected landscape picture on it was ordered for the participant through the online retailer.

Participants performed three tasks during our experiment: (1) a liking rating of the landscape photographs (on a PC in a laboratory), (2) choice from different-sized sets of landscape photographs (in the fMRI scanner), and (3) responses to a paper-based questionnaire (in the lab outside the scanner) regarding choice experience.

During the *liking rating task* participants were shown the landscape images one by one on a computer screen and had to state how much they wanted to have each of those pictures printed on the product of their choice by setting a bar on a 10-point scale (with "1" meaning "I would not like at all to have the picture on my selected item" and "10" meaning "I would like to have the picture on my selected item very much.").

Images presented to participants were versions of high-resolution landscape photographs[15]. Landscape images were assigned to 6 categories: mountains, lakes, dunes, waterfalls, forests and beaches. Each category included 52 pictures (the total sample of images consisted of 52*6=312 pictures).

Images were presented in a random order, and subjects had to rate each image twice in two successive rounds. The second round started immediately after participants had completed rating all the pictures for the first time. Subjects could use as much time as they wanted to give their ratings. The final rating of each image was determined by taking the average of subjective ratings given to each image by participants in two successive rounds. To familiarize subjects about the types of images to be presented, and to help them assess a distribution of subjective ratings of these images, there was a short training session prior to the actual rating session. Training involved 12 pictures that were not used in the actual experiment. Also in the training procedure pictures had to be rated in two successive rounds.

Subjects' ratings of the individual images served as a base for creating the choice sets presented to the participants in task two.

During *the choice task* of the experiment participants examined the sets of images and decided which of the landscape pictures they wanted to have printed on the product of their choice. This task was conducted in an MRI scanner[16]. Apart from measuring brain activity we also tracked eye-movements of each subject. For detailed description of equipment and data acquisition, please, see Appendix 3.A.

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[15] All the images were obtained from the same webpage (www.terragalaria.com) with the permission of the author.
[16] For a complete review of fMRI methodology, see Huettel, Song, & McCarthy (2004).

Table 3.1 summarizes choice conditions subjects faced during this task. The choice sets differed on two dimensions: the number of alternatives and the availability of a clear favorite item in the set. With regard to the number of alternatives, choice sets presented to participants included 6, 12 or 24 visible images of the same category. With regard to the availability of a clear favorite item in a set, there were two types of sets: choice sets with a **c**lear **f**avorite item (CF sets; the difference in rating between the first and the second best item in these sets was large), and choice sets with **n**o clear **f**avorite alternative (NF sets; the difference between the first and the second best item in the sets was small and not pronounced). To create the **CF** and **NF** we used subjective ratings of images made by participants in the liking rating task of the experiment.

In addition, in some trials subjects could select a photograph by themselves ("free" choice trials), while in other trials a landscape picture from a set was selected by the computer for the participant ("forced" choice trials). Thereby the computer would always select a "good" or preferred picture ranked as 1^{st} or 2^{nd} in the "forced" set.

All forced choice sets (FO) were sets without a clear favorite picture, while free sets could be both, with (CF) or without (NF) clear favorite alternative.

Choice sets were presented on an otherwise black screen with a central, white fixation cross. Items of the choice sets could be randomly placed at 15 possible positions to each side of the fixation cross. On both sides these positions were arranged in five rows and three columns. Depending on the condition, a certain number of visible landscape images was placed at these positions (with an equal amount placed to the right and to the left side of the fixation cross). Scrambled images were presented at the remaining locations in order to diminish global visual differences between sets (luminance, color, image density etc.).

Table 3.1: Experimental conditions and number of trials in each condition during the choice task in fMRI scanner.

Number of visible landscape pictures (other blurred)	**Free choice** (the choice has to be made by the subjects)		**Forced choice** (FO) (the choice is made for the subjects by a computer)
	Sets with clear favorite item (CF)	**Sets with no clear favorite item** (NF)	**Sets with no clear favorite item**
6	8 trials	8 trials	8 trials
12	8 trials	8 trials	8 trials
24	8 trials	8 trials	8 trials

Examples of the computer screens presented to the participants during the fMRI experiment are shown in Figure 3.1.

No choice set included identical alternatives. Moreover, within each experimental session/run an item was shown only once and, across sessions, choice sets would always comprise different items.

Each trial in the choice task consisted of three stages: an *exposure stage* (10 sec) – during which participants were exposed to the set of the images for the first time[17]; a *delay stage* (13-14 sec) - during which subjects saw a black screen with the central fixation cross and had to maintain fixation on it; and a *response stage* (3 sec) – during which the screen with the same choice stimuli appeared for the second time and subjects had to indicate the selected item. The three-stage paradigm which subjects faced in the fMRI scanner (exposure, delay and response period) was borrowed from Rosenbaum (1980) and allows teasing apart brain

[17] Choice set presentation was followed by a brief random-dot mask that was presented for 0.5 seconds. The mask aimed to prevent specific after-images of the choice stimuli.

Figure 3.1A

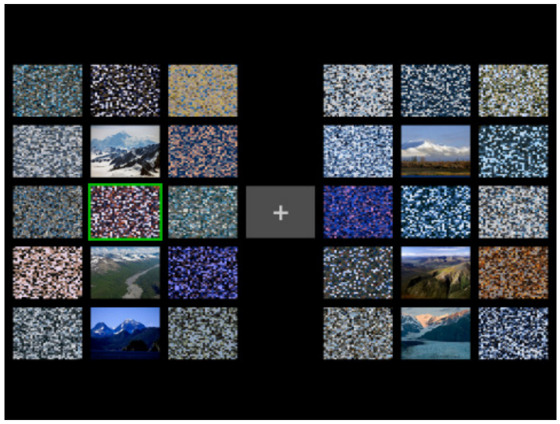

Figure 3.1B

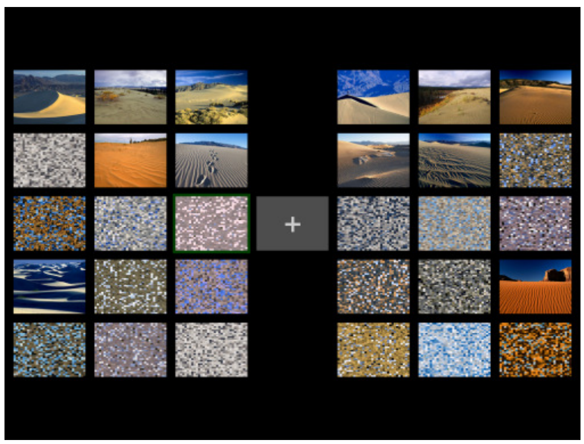

Figure 3.1C

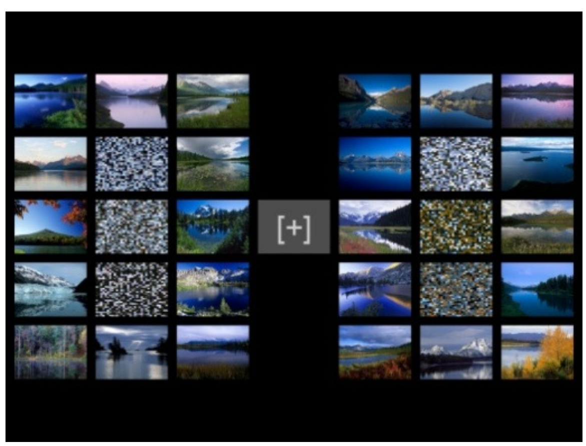

Figure 3.1: Examples of screenshots for the set containing: A. 6 items; B. 12 items; C. 24 items.

activity related to viewing/choosing and physical selection of a chosen item (i.e., movement itself and its preparation). Between each trial subjects saw a black screen with the fixation cross on it (13 sec) and had to maintain gaze on that fixation cross. The black fixation screens between trials were considered the baseline in our analysis. The exact timeline of the choice task is presented in Figure 3.2.

Subjects selected an item using the thumb of their right hand on an MRI-compatible button-box (see full description of equipment in Appendix 3.A). To familiarize themselves with the task, subjects went through a short training prior to starting the actual choice session. During training we presented only choice sets that were not used in the actual experiment.

The landscape picture selected (by or for participants) in each trial affected the image that a participant received printed on the product that s/he had selected. In particular, at the end of the experiment, the computer selected one trial at random from all the trials that a participant faced during the experiment. The landscape that was chosen in that trial was then used to produce a featured product (i.e., printed on a product of the participant's choice). This product was sent to the participant about a week after the experiment[18].

We used an event-related fMRI-design for the imaging part of the experiment. This choice task of the experiment consisted of four runs (sessions) with short breaks between runs (< 5 minutes). Each participant went through 72 trials (i.e., faced 72 different choice sets and had to make either a free or forced selection in each of them) with 18 trials in each run. The design was entirely balanced with 24 trials of each set type (i.e., 24 forced sets, 24 free CF sets, and 24 free NF sets). Participants faced eight trials of each set size for each choice set

[18] If a participant did not make a choice in a trial, the computer deducted $3 from the experimental payoff if the trial with no choice was selected at the end. To create a featured product, a new trial would be then again selected at random and the picture chosen in that trial would be printed on the good selected. However, this never happened during the experiment.

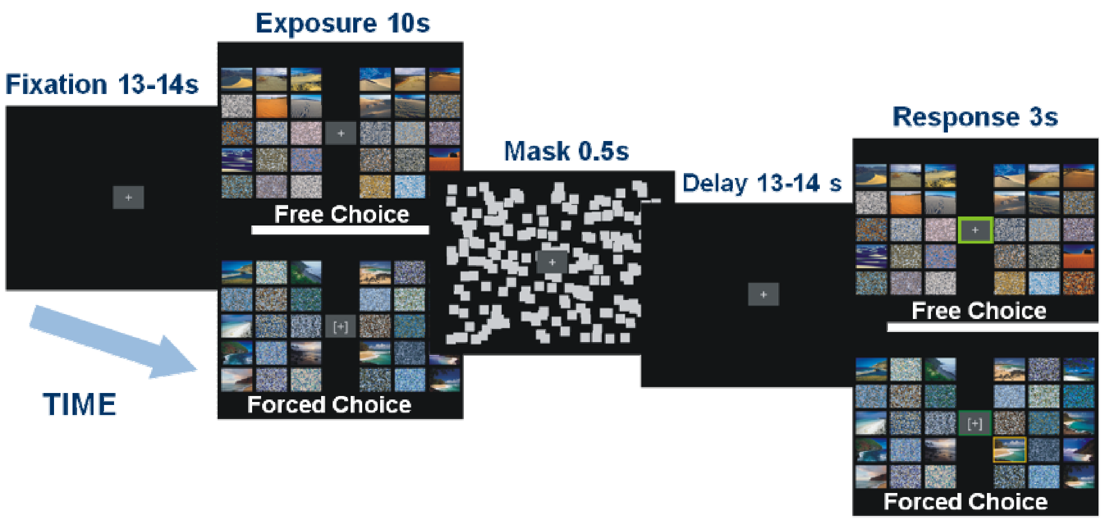

Figure 3.2**:** Timeline of the choice task in the fMRI scanner.

type (i.e., out of 24 CF sets, subjects faced eight 6-option sets, eight 12-option sets, and eight 24-option sets), see Table 3.1. The landscape categories (lakes, mountains, etc.) were presented in a random order to the participants. All 72 trials were presented to each participant in an individually randomized order.

During *the questionnaire task* of the experiment participants filled in a paper-based questionnaire outside the scanner. We assessed subjective value of the set by asking participants whether they felt that each choice set size contained the "right" amount of alternatives (answers were given on a 9-point scale with 1 "No, I had too few choice options", 5 "Yes, I had just the right amount of choice options", and 9 "No, I had too many choice options")[19]. Subjects also reported how difficult it was for them to choose from each choice set size (from 1 "Not difficult at all" to 10 "Extremely difficult").

The experiment lasted about 90 minutes in total.

Subjects. 20 healthy individuals (65% males, mean age 26.1) participated in this study. In addition to the customized product, each participant received a cash remuneration (40 US $

[19] Participants were asked many questions, but we report only those that are relevant to this paper.

if they chose a desk organizer, bag, or apron; and 50US $ if they chose a mug, mouse pad, or T-shirt). All subjects were right-handed and had normal (or corrected to normal) vision. Participants signed the informed consent form prior to participating in the experiment. The study was performed in accordance with the declaration of Helsinki and the Caltech Institutional Review Board guidelines[20].

3.4 Results

In this paper we focus our analysis on the exposure period of the choice task. Presenting data obtained during the delay and response phases is beyond the scope of this paper.

3.4.1 Behavioral and eye-tracking results

Before turning to brain activity, we first describe the eye-tracking and behavioral results. Overall, subjects indicated that they liked the selection of images that they were choosing from (on the 10-point scale: M = 7.16, SD=1.57) and found the process of choosing enjoyable (on the 10-point scale: M = 7.32, SD=1.33). Several subjects also indicated verbally or in their written comments that the experiment was “engaging”, “cool”, and “interesting”. These data confirm that subjects were not indifferent to the images they were exposed to, and that the choice task was engaging (with the exception of one subject)[21]. For the descriptive statistics of the liking ratings of individual images, refer to Appendix 3.B.

[20] One subject went through the rating procedure, but could not enter the MRI scanner due to unexpected claustrophobia. That subject therefore could not participate in the rest of the experiment and is not counted here. She received the show-up fee for the first part of the experiment ($20) and was not included in the analysis.

[21] One subject reported verbally that he was indifferent about landscape images, was not interested in choosing any of them, and even rejected to receive the customized item at the end of the experiment. His ratings of the

The data demonstrate that the number of saccadic eye-movements as well as subjective choice experience was influenced by the number of alternatives in the set. The number of saccades per second increased with the number of items in the set in the exposure period, see Figure 3.3. Subjects made significantly more eye-movements in the 12- as opposed to 6-item set condition ($t = 10.11$, $p < 0.001$). The number of saccades per second increased further in the 24 as opposed to 12-item sets ($t = 6.68$, $p < 0.001$). Moreover, subjects made significantly more saccades per second in free than in forced choice trials regardless of the set size ($t = 4.38$, $p < 0.001$). Previous research has demonstrated that the number of eye-movements correlates with shifts of attention (for further discussion, see Wedel & Pieters, 2007). Therefore, one may conclude that "attention load" increases with the set size, and is higher in the free than in the forced choice trials. These data confirm that subjects were more involved in the task and also had to "work harder" to make the selection in the free than in forced choice trials.

Subjects' perception regarding the value of the set was also affected by the number of alternatives which the set contained. Recall, that a subjective set value was measured by responses given on a 9-point scale (where "1" meant subjects felt they had too few, "5" - just the "right" amount, and "9" - too many options to choose from). For easier visualization of the results, we transformed the original scale into the new one by doing the following calculation: [5-("Subject´s Perception of Set Value" -5)]. On the new scale "5" would represent the "optimal" set size, or the highest value of the set, while every number below 5 would show

landscape indicated the same: there was no variability in the liking ratings of different images that he reported. Over 84% of images were given a rating of "0" (meaning, the subject did not like the images at all), and the rest 16% of ratings were distributed between 0 and 1.8 on the 10-point scale ($M = 0.1$, $SD = 0.28$). The data clearly indicated that the task was not engaging for that particular subject. Therefore, the data from that subject was not included in further analysis (behavioral or fMRI), and analysis was performed on the data obtained from the remaining19 participants.

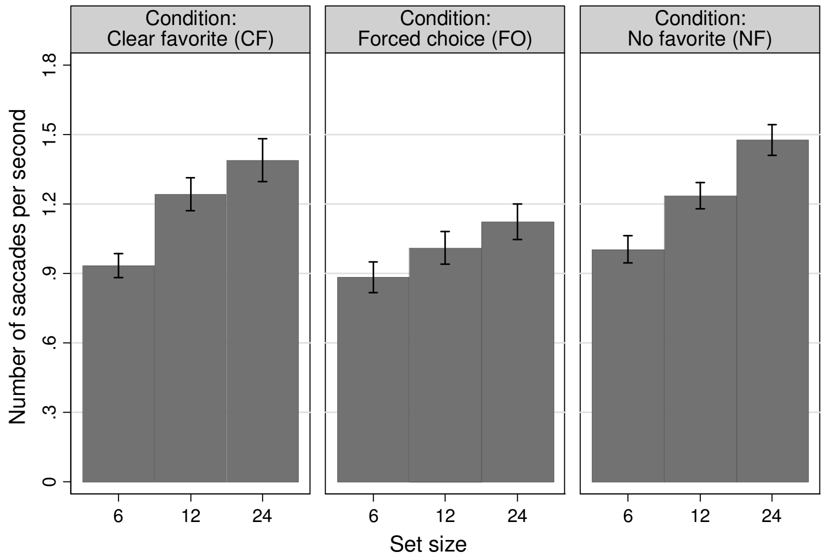

Figure 3.3: Number of saccades per second during the exposure phase of the choice task.

that the set value is lower than “optimum”. The data demonstrate that sets with 12 alternatives were considered optimal, as, according to the reports, they had about the “right number of items” (M=4.68, difference from “5”: t = 1.10, p = 0.285). Smaller and larger sets were of less value for the subjects: sets containing 6 items were seen as having “too few alternatives” (M= 4.05, difference from “5”: t = 3.83, p < 0.001), while large sets with 24-items were seen as including “too many items” (M = 2.79, difference from “5”: t = 6.71, p<0.001). In other words, Figure 3.4A demonstrates that the subjective value of the choice set is an inverted U-shaped function of the number of choice alternatives, peaking for sets which contained 12 alternatives.

Choosing from the larger sets was also more difficult. Subjects found it more difficult to choose from 24 than from 6 or 12 alternatives (t = 4.15, p < 0.001, t = 5.08, p < 0.001, respectively). Therefore, difficulty is an increasing function of the number of items in the set, see Figure 3.4B.

Figure 3.4A

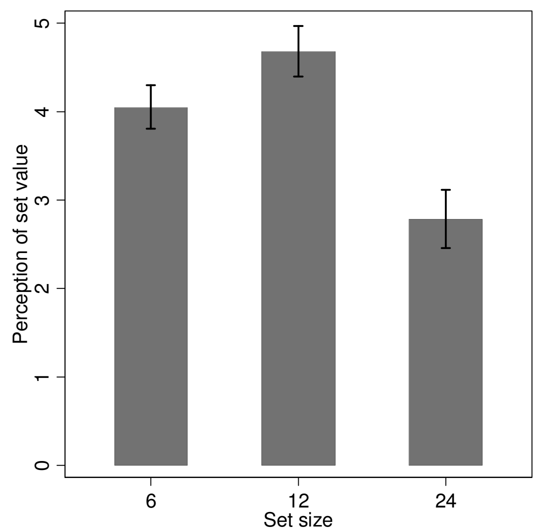

Figure 3.4B

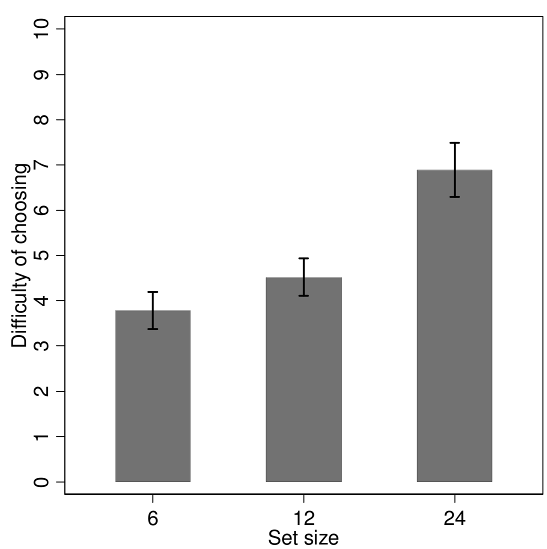

Figure 3.4: Subjective ratings of participants regarding their choice experience. A. Choice set value by set size; B. Difficulty of choosing by set size.

3.4.2. Brain-imaging results

We performed functional image analyses both at the individual- and group- level.

On the individual level we used two different models to account for different aspects of fMRI-response characteristics.

In model 1, on the individual subject level (1^{st} level) 9 experimental conditions were modeled separately [3 tasks (CF, NF, and FO choice) x 3 task stages (exposure and mask, delay, and response periods)] in the general linear model (GLM). The model also included three further parameters which served as additional parametric modulators for each of the 3x3 regressors of the GLM: number of items in the choice set (linear and squared term), and liking rating of the chosen item (linear term). We used a polynomial of the second order to model the response function because, based on the behavioral ratings from previous research and our own results, we expected to find an inverted-U response of the brain activity to the number of items the subjects faced.

For the group-level (2nd level) analysis we explicitly masked the brain with the task related areas. On the group-level, contrast images for the various conditions were analyzed using t-tests and multiple regression analysis. In this analysis we always present the results for three statistical thresholds: $p < 0.01$, $p < 0.005$ and $p < 0.001$ (uncorrected) to emphasize the spatial specificity of our results.

The 2nd level analyses of the results of model 1 allowed us to map brain regions which showed: first, an inverted U-pattern in response to the number of items in the set (i.e., the squared signal component was significantly larger than the linear signal component); second, an increasing trend in response to the number of items in the set (i.e., the presence of a linear signal component that significantly differs from baseline); third, significant differences in activity in free (NF) as opposed to forced trials (FO); fourth, significant differences in activity when subjects faced CF as opposed to NF sets; and finally, significant correlation with the liking-rating of the item chosen in each individual trial.

In model 2, on the individual subject level the GLM included regressors for each of our 3x3 experimental conditions [3 tasks (CF, NF, and FO choices) x 3 choice sets (6-,12-, and 24-item sets)] and for each stage of the task (exposure and mask, delay, and response period).

The 2nd level analyses of model 2 allowed mapping brain regions that were significantly correlated with: first, the number of saccades; second, subjective ratings given by the subjects about the value of the set; and third, subjective ratings of difficulty of choosing from each set.

Thus, while the analysis of the model 1 captured aspects directly related to the task itself – the number of alternatives in the set, the value of the selected item in each trial etc. – the model 2 would rather focus on aspects that were not only task-related but also differed between individual subjects, namely the number of saccades per condition and the subjective ratings about set value or difficulty of choosing. Note, that capturing all of these aspects in a single model either would have reduced the statistical power (due to pooling) or, alternatively, would have led to an overfitting of the data. In order to still allow a direct comparison of the results obtained with the two models, we did an additional descriptive ROI-based statistics described below.

In addition, we extracted normalized beta weights for the exposure-period regressors of the second model for a 3mm-radius sphere that was centered on functionally defined regions of interest (ROIs): those regions that exhibited significant fMRI-signal components correlated with either the linear term, the squared term (both model 1) or the amount rating (model 2).

After extracting the normalized beta weights, we performed multiple correlations of these beta values with: first, subjective ratings of the choice set value; second, subjective ratings of difficulty; third, number of saccades; fourth, linear term for the number of items in the set; and finally, the squared term for the number of items. In addition, the statistical comparison for CF > NF and NF > FO conditions within ROIs was based on those extracted beta values. More precisely, we performed paired t-tests across individual subject's beta values for the respective conditions (one-tailed).

We first determined the task-related areas, i.e. areas that were involved in all free choice tasks relative to the baseline condition during the exposure period (contrast: Free Choice (both CF and NF) > Baseline). Task related areas are shown in Figures 3.5, 3.6 and 3.7. Overall, the whole brain analysis of the fMRI data revealed that parietal, occipital, anterior cingulate, premotor, prefrontal and orbitofrontal components as well as basal ganglia, were activated. Activation of each particular area was modulated by the specific tasks in each condition and is described in detail below.

3.4.2.1 Physical reaction to the number of choice options.

BOLD activation in the occipital cortex [lingual gyrus (LG; BA 18) also encroaching fusiform gyrus ; inferior occipital gyrus (IOG; BA 19); and middle occipital gyrus, (MOG; BA 19)], parietal cortex (SPL; BA7), and premotor cortex [bilateral activity both in dorsal premotor cortex (PMd, bilateral; BA 6), and supplementary motor area (SMA, bilateral)] increased linearly in response to the increase of the number of items in the set (i.e., activity was modulated by the linear parameter of the number of items in the set; Linear > Baseline contrast, model 1), see Figure 3.5A-E[22]. Most of the areas activated in that contrast have been shown to be modulated by motor planning and execution and processing of visual scenes in primates and humans (see e.g., Andersen & Buneo, 2002; Grill-Spector & Malach, 2004;

[22] Appendix 3C shows exact coordinates of the brain regions and statistics associated with their activity.

Orban, Van Essen, & Vanduffel, 2004; Medendorp et al., 2008). Therefore, the increased activation in these areas might reflect costs of facing the large choice sets.

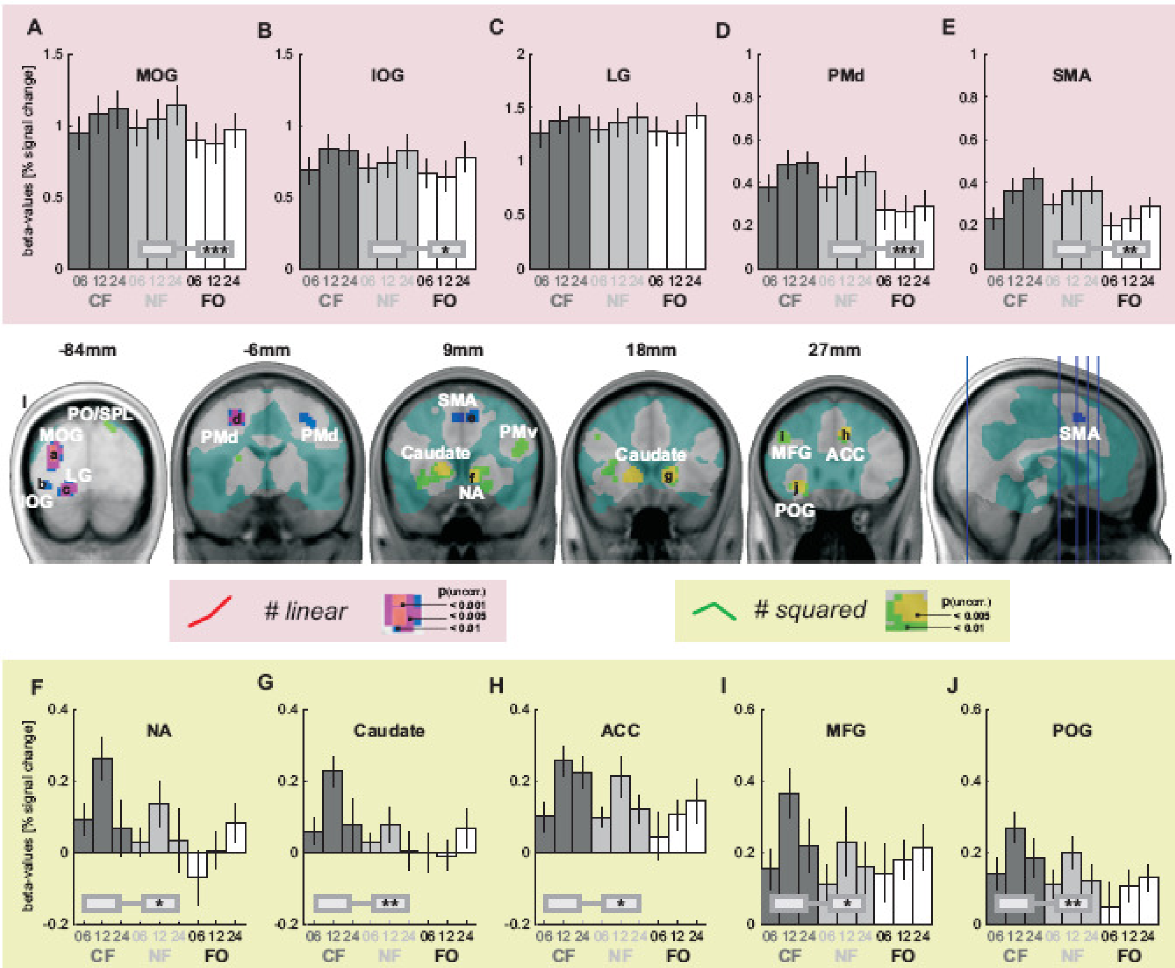

Figure 3.5: Brain activation in Linear > Baseline (A-E) and Quadratic > Linear (F-J) contrasts, model 1.

While activity in some brain regions increased linearly with the number of choice alternatives, BOLD activation in the other regions has an inverted "quadratic" response to the increase of the choice set size. Activation in the anterior cingulated cortex (ACC; BA 32), dorsal striatum (bilateral activity in the caudate with some encroachments into the putamen), ventral striatum (NA), medial frontal gyrus (MFG; BA 44-46), posterior orbitofrontal cortex POG (BA 47), ventral premotor (PMv; BA6), parieto-occipital transition area (POTZ), and superior parietal lobule (SPL; BA 7) was significantly correlated with the squared term for the number of items in the choice set (i.e., it was significant in the "Quadratic term" > "Linear term" contrast, model 1). Curiously, the activity in these areas did not increase monotonically with the number of options; rather it followed an inverted-U trend as the choice set size increased.

As the number of items in the choice set increased from 6 to 12 alternatives, activity in these brain areas also increased (reaching its peak when subjects faced medium-sized sets of 12 items). However, as the number of items increased further - from 12 to 24 items - activation in these brain regions leveled off, see Figure 3.5F-J.

Many of the brain areas activated in this contrast have been previously associated with value, reward or cognitive effort/control. The caudate, NA, and POG have been found in previous studies to respond to rewards in monkeys and humans (O'Doherty et al., 2001; McClure, Berns, & Montague, 2003; O'Doherty, 2004; Knutson et al., 2008; Rushworth et al., 2008). Therefore, it is highly likely that activity in these regions reflects "reward" one obtains from facing one or another choice set size. The activity in these areas is increasing at the beginning, suggesting that facing medium-sized sets might be more "rewarding" than being confronted with smaller sets containing only 6 items. However, there is a limit to how much choice is "rewarding". The activity in the areas associated with reward starts to decrease when the set gets larger and subjects experience "choice overload."

The MFG was previously shown to play a crucial role in sustaining attention and working memory, cognitive control, and especially implementation of control (Cohen et al., 1997; Fletcher, Shallice, & Dolan, 1998; Bechara et al., 1998; MacDonald III et al., 2000).

Therefore, it is highly likely that MFG activity in our case demonstrates how much attention and working memory is involved in choosing from different sized sets, i.e., it reflects how "motivating" each choice set size is. When the choice sets are small the cognitive strain imposed on decision-makers is low and associated MFG activity is also low. With the increase of the choice set, load on attention and working memory should increase. Interestingly, this happens only to some extent. When the choice set becomes extremely large, people may simply "give up" investing attention and capacities of working memory deteriorate.

The data also confirm our expectations regarding ACC activity, which has been claimed to represent the "integrated" action value, i.e., value which is based on the cost-benefit analysis (Kennerley et al., 2006; Rushworth et al., 2007; Rushworth & Behrens, 2008). The authors suggest that the ACC is essential when one makes decisions about how much effort to invest to receive a reward. Our results are consistent with this proposition. As expected, and as shown by previous research (Reutskaja & Hogarth, 2006; Shah & Wolford, 2007) medium-sized sets are the most motivating and satisfying (i.e., they should be associated with the highest reward). Inverted-U activity in the ACC peaking at medium-sized sets might reflect that subjects are willing to invest the greatest amount of effort when facing intermediate sets, while lower effort when facing larger and smaller sets.

It is important to note that the activity correlated both with the linear and quadratic terms is stimulus-driven, i.e., is correlated with the actual number of the items in the choice set (either with the linear or quadratic term representing the number of items). However, behavioral data suggest that subjects' perception about the choice set value and difficulty of choosing from these sets also differed depending on the choice set size. Does the subjective experience of the decision process also modulate brain activity? If so, how is this subjective experience represented in the brain? Do these subjective perceptions about the set value and difficulty of choosing modulate activity in the same regions where we found the stimulus-driven physical reaction to the number of items? To answer these questions we conducted further analysis, using model 2.

3.4.2.2 Neural correlates of perceived difficulty and subjective set value

Subjective perceptions of difficulty from choosing modulated brain activity (model 2). Recall that the self-reported difficulty increased with the number of items in the set. Activity in the cingulate cortex (medial part of the CC and ventral ACC), SMA, LG, MOG, PMd (bilateral), PMv, MFG, caudate, and thalamus was significantly correlated with the perceived difficulty, i.e., increased with the number of alternatives in the set (see Figures 3.6E & 3.7A). Brain regions activated in that experimental contrast were similar, but not always identical to the regions where activity was correlated with the linear term in model 1 (see Figures 3.6A, 3.6E, and 3.8). Some subregions of the SMA; PM cortex, and LG were activated in both contrasts (i.e., their activity increased with the linear term in model 1, and showed significant correlation with difficulty ratings). On the other hand, activity in other subregions of the SMA and PM cortex as well as areas such as the thalamus, cingulate cortex and MFG was modulated by subjective perception of difficulty, but not by actual number of choice alternatives.

The phenomenon of choice overload was also reflected in subjects' feelings about the set value. Recall that we asked participants directly to determine a subjective value of the set, or report how they felt about the number of alternatives in different sets. Intermediate sets had greater value for participants than large and small sets. Areas exhibiting fMRI-activity which was correlated with the subjective value of the choice set were mapped within the medial aspects of right superior parietal lobule -- SPL -- (model 2, see Figures 3.7A and 3.9), which

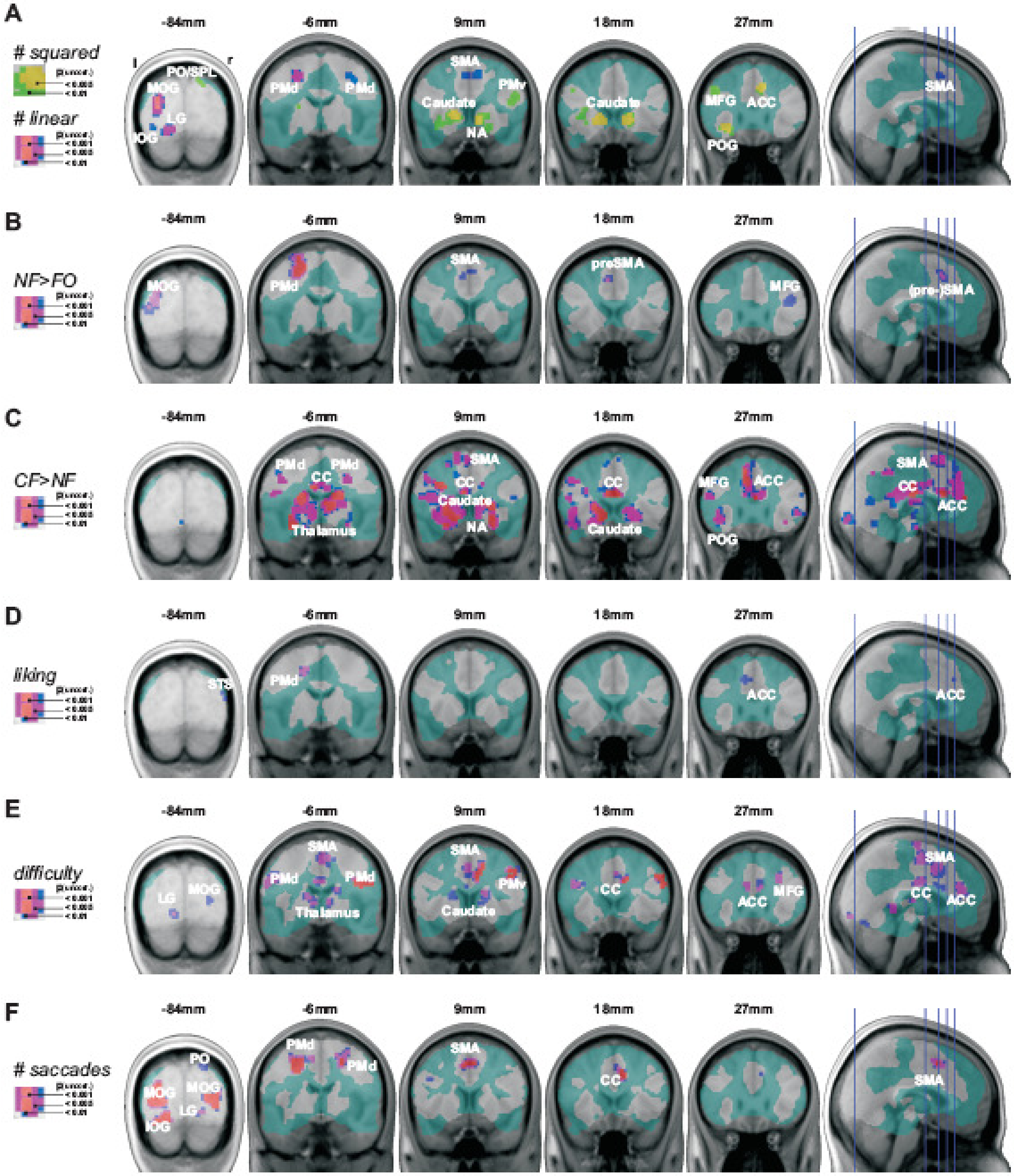

Figure 3.6: Neural correlates of choice in various contrasts (or correlations with indicated variables). Contrasts A-D are based on results from model 1; contrasts E-F are based on results from Model 2.

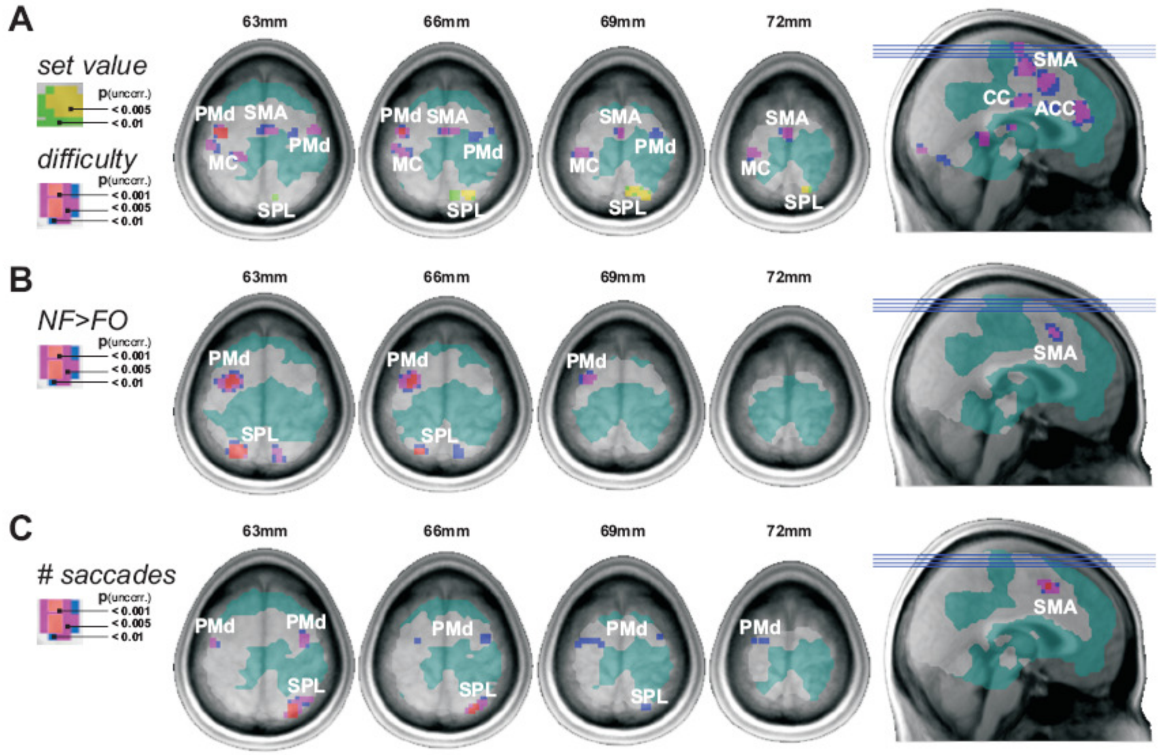

Figure 3.7: SPL activity in different experimental conditions.

was shown to respond in monkeys and humans to value and choice behavior (Platt & Glimcher, 1999; Cui & Andersen, 2007; Pesaran, Nelson, & Andersen, 2008). Interestingly, SPL activity did not increase monotonically and rather resembled an inverted-U pattern. The highest activity was associated with the highest subjective value of the set and was found when participants faced sets with 12 options. Lower activity and lower subjective value were associated with smaller and larger sets.

It is worth noting that areas, in which activity was correlated with the quadratic term in model 1, did not show significant correlation with "subjective" set value[23] in model 2.

[23] The opposite, however, was not true. The SPL, activity in which was correlated with the subjective set value, also showed significant inverted-U activity in the Linear term >Baseline contrast (model 1), though at a very low threshold (p< 0.05, uncorrected).

Therefore, our data suggest that the "subjective" set value might be represented in a separate brain region, namely SPL.

Our data also demonstrate that the number of saccades increased with the number of items in the choice set. Areas exhibiting fMRI-activity which was correlated with the number of saccadic eye-movements included the SMA, PMd, MOG, IOG, LG, PO, medial parts of CC, and lateral parts of SPL (analysis based on model 2), see Figure 3.6F. Eye-movements have been shown to reflect covert attention (for further discussion see Wedel & Pieters, 2008).

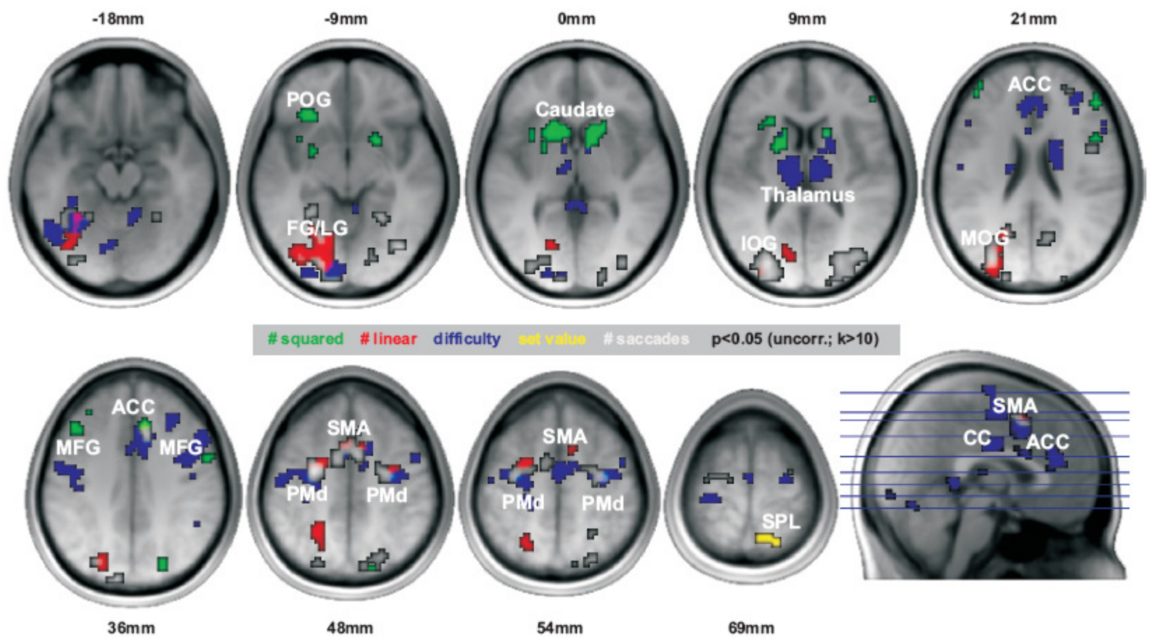

Figure 3.8: Comparison of brain activity in the following contrasts: Linear term > Baseline (# linear, model 1); Squared term > Linear term (# squared, model 1); significant correlation with difficulty (difficulty, model 2); significant correlation with subjective ratings of the set value (set value, model 2); subjective correlation with the number of saccades (# saccades, model 2).

Moreover, brain regions where activity was correlated with the number of saccades were almost identical to those where activity was correlated with the linear term in model 1 (i.e., see Figures 3.6A, 3.6F, and 3.8). Some subregions of the SMA; PM cortex, LG; and CC were also mapped at locations similar to those of regions, in which activity was correlated with difficulty ratings (see Figures 3.6E and 3.6F; 3.7A and 3.7C; 3.8). Therefore, activity in the areas listed above, which is increasing with the number of items, might represent cost of facing different-sized sets and reflect attention load that increases with the number of options in the set.

Activation in the ACC, dPM and STS was correlated with the liking rating of the chosen item (analysis based on model 1), i.e., activation in these areas increased with the

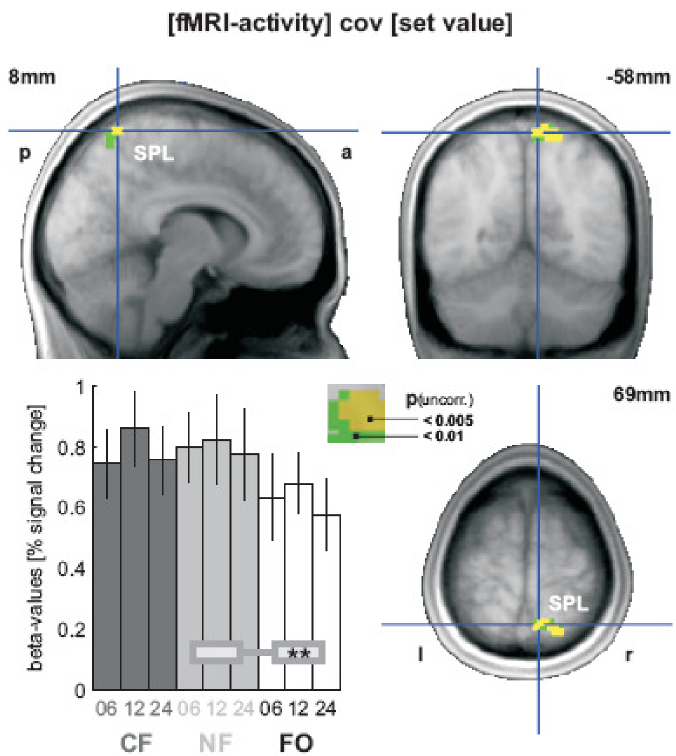

Figure 3.9: Choice set value representation within the SPL.

rating of the chosen item, see Figure 3.6D. Interestingly, this activation was detected during the exposure period, relatively long time before the subjects revealed their actual selection (i.e., around 15 seconds prior to the selection).

The results show that both the actual number of items in the set as well as perceptions of choice experience modulate brain activation. Until now we conducted analyses independent of whether the subjects faced forced or free choice trials or whether the choice set contained their strongly preferred item. The marketing and behavioral literature, however, suggests that these two variables may affect perception of variety. Our behavioral results also showed that the participants did not treat sets in free vs. forced as well as in CF vs. NF trials as identical, and it is also important to understand the neural correlates of these differences. In the following section we discuss how availability of a clear item in the set and choice freedom affect neural representations of choice from multiple alternatives.

3.4.2.3 Neural correlates of the availability of a clear favorite alternative in the set and of choice "freedom".

Brain activity was modulated by the presence of the favorite item in the set (overall). Many of the areas that showed an inverted-U activity in the free choice tasks also showed significant activation in the CF > NF contrast, compare Figures 3.6A and 3.6C [as a test, note the areas that showed significant activation in the CF > NF contrast are almost all in good statistical correspondence with the areas that showed an inverted-U activity].

The most pronounced activity that shows the difference in the CF > NF contrast was found in the caudate (bilateral), an area that has been associated with reward in previous research (Knutson et al., 2001; O'Doherty et al., 2001). However, this activity is not restricted to the caudate only, rather it invades other neighboring components of the basal ganglia (e.g., the pallidum).

We also compared fMRI-signal change in task-related ROIs which were significantly correlated with the quadratic term in model 1. The analysis revealed significantly higher activation in the CF as opposed to the NF sets for each area that has been found to correlate with the quadratic term (see Figure 3.5F-J). In many cases BOLD activity associated with choosing from the large CF sets was often as high as that associated with choosing from the medium-sized NF sets.

This finding goes in line with previous research in marketing, which showed that an “ideal point availability” simplifies choice from large sets (e.g., see Chernev, 2003). Our results offer putative neural bases for this proposition. When the set contains an optimal item, it is also associated with greater activity in areas, which have been shown to reflect reward or value processing compared to the case when an optimal item is absent.

This finding implies that large sets are not always “bad” or “overwhelming”. Large sets could be as rewarding as medium-sized set, if an “ideal” option is present in the set. The data suggest that the benefits of having an “ideal” item within the set might compensate the costs of overwhelming set size.

Brain activity was also modulated by choice “freedom”. Activity in the posterior parietal cortex (PPC region) [bilateral activation in the medial aspects of superior parietal lobule (SPL)], PMd, SMA and MFG was significantly higher in the free choice as opposed to the forced choice trials, see Figures 3.6B and 3.7B. (NF > FO contrast, model 1).

It is worth noting, that some areas, in which activity followed an increasing linear pattern and was correlated with difficulty, also showed greater activation in the free as opposed to the forced choice trials, see Figure 3.6A, B, E. We also compared percent signal change for task-related ROIs, which were significantly correlated with the linear term in model 1, in the free and forced trials. Brain activity for each of these ROIs was significantly higher in the NF condition than that in the FO condition with the exception of a nonsignificant difference in activity in LG (see Figure 3.5A-E). Overall, our findings suggest that "free" choices are also more difficult and demanding for the human brain.

Interestingly, the activity in regions, which followed an inverted U-trend in free choice trials, had a linearly increasing trend in the forced choice condition (see Figure 3.5F-J). If activity in regions such as the NA, caudate, and POG is modulated by "reward" (which is highly likely in our case), then the activity in these regions should increase with the number of choice items in the forced trials. In the small sets, the benefits of having a freedom of choice are greater than the costs of choosing, therefore, small "free" choices are more rewarding than small forced choices. However, when the choice set is large, difficulty of choosing might outweigh the benefits of freedom of choice. When the set size increases from medium to large size, "reward" associated with free choices decreases, while "reward" associated with forced choices "increases".

ACC activity, which is increasing with the number of items in the forced sets, might also reflect the highest net value from larger than from smaller forced sets. Indeed, when the choice is done by someone else the probability of obtaining a better option from a large set might be greater than from a smaller set (simply, because there are more options which are closer to the one´s preferences), and the underlying cost-benefit analysis in the ACC might reflect these calculation.

3.5 Discussion

In this paper we explored the neural bases of human decision making when people are confronted with choices from different-sized sets. Our data demonstrates that brain activity was modulated by the number of choice alternatives available to the participants, by subjective perceptions about choice experience, by availability of a strongly preferred item as well as by the “freedom of choice”.

BOLD activation in the LG, IOG, MOG, SPL, PMd, and SMA, showed a linear increase when the number of options in the choice set increased. The increasing activity by the set size in those areas is to be expected, as these areas were shown to be involved in preparation and execution of movements and saccades in previous research. As the number of items in the set increases, task demand imposed on a human being should also rise: e.g., one needs to make more saccadic eye-movements and put greater effort in movement planning, which might be reflected in visual and motor processes. Therefore, we argued that linearly increasing activity in these areas might reflect the “cost” of having more choice. Activity in most of these areas was not only correlated with the actual number of choice items, but also with subjective difficulty ratings that participants assigned to different-sized sets. Our data also show a clear evidence of choice overload phenomenon in the brain. Activity in the ACC, caudate, NA, MFG, and POG followed an inverted U-pattern with the increase in the number of choice alternatives. The activity in these regions increased when the set size increased from 6 to 12 items, and then leveled off when the set sized increased further from 12 to 24 alternatives.

Interestingly, many of the brain areas demonstrating an inverted-U activity in response to the number of items in our task, have been associated with the processing of reward or cognitive effort in previous research. Therefore, we attributed activity in these regions to the “net reward”, one obtains from facing one or another choice set size. The subjective set value, on the other hand, was mapped within the SPL, and followed and inverted-U pattern.

We also found, that two other variables – “freedom” of choice and availability of strongly preferred set might affect neural representations of choice from multiple alternatives.

Interestingly, many of the areas where activity showed an increasing linear trend and was correlated with subjective difficulty, also showed a significant activation difference in the free as opposed to forced choice conditions. The data suggest that more “resources” are necessary for performing free as opposed to forced choices. This is consistent with many behavioral findings, which claim that though people prefer to have freedom of choice, they often find it extremely difficult to decide what to choose, something that Schwartz (2000) named a “tyranny of freedom”.

In addition, regions associated with reward and value, and show an inverted-U pattern activity, also showed greater activation when the set contained a strongly preferred item. If a clear favorite alternative is present, choice becomes more “rewarding” and reflects greater value than in the case when such an alternative is absent. Therefore, in many cases, choosing from the large CF sets becomes as “valuable” and “rewarding” as choosing from the medium-sized NF sets.

Though more research is needed to investigate this issue in-depth, we speculate that our results might suggest that marketing actions may affect neural correlates of the net value of the set. Previous research has demonstrated the impact of marketing actions on neural activity. Plassmann et al. (2008) has found that marketing actions, such as change in price, can modulate the neural representation of experienced pleasantness. Our results suggest that the availability of a “clear favorite” alternative can modulate reward-related areas. People are, therefore, able to deal with more items without losing “reward” from the process of choosing if a strongly preferred item is present in the set.

Interestingly, some of the brain areas, activity in which was associated with the increase in the number of choice options in the study by Marsh et al. (2007), also appeared to have differential activity modulated by the number of choice alternatives in our experiment (e.g., dACC, caudate, MFG). Moreover, Marsh et al. (2007) also found that the caudate, dACC and FMG responded *similarly* to the change in the number of decision items, i.e. the activity in these regions increased with the number of response options. These authors suggest that these brain regions might function “in coordinated fashion” (p. 986, Marsh et al., 2007). Our data are compatible with this suggestion. These three brain areas also responded similarly to the choice task in our experiment. However, in comparison to the study of Marsh (2007), activity in these regions was not monotonically increasing with the number of choice items, rather it followed an inverted-U trend. We stress that our results are not contradictory to those of Marsh et al. (2007) and rather support them when the choice sets are small [recall that in Marsh et al. (2007) study the number of items increased from two to four only]. As we expected, our data suggest that the areas where activity showed significant correlation with the quadratic term of the number of items, might also reflect how “rewarding” *the entire choice set* is. In addition to simply being associated with a reward from a single item or stimulus (a result reported in previous research), our results might suggest that the activity in these areas is also mediated by the objective “net value” from facing the entire set (i.e., not a value of a single item, but an integrated value of several items at a time). This is the first study, to the best of our knowledge, which explicitly demonstrates this function of these areas.

Two brain regions, namely the ACC and SPL, deserve special attention. The data confirmed our expectation that the ACC followed an inverted-U pattern with the increase of the number of items in the set. We based our proposition on the claims that the ACC plays a crucial role in “naturalistic situations” when the environment is changing, and is important for action selection, i.e., when one makes decisions about how much effort to invest to receive a reward (Walton et al., 2007; Kennerley et al., 2006; Rushworth et al., 2007). Therefore, the

ACC might be making cost-benefit analysis prior to a decision. Our results were consistent with this proposition.

Activity in the dACC may represent the "net" reward or value of the set, which is based on the underlying costs and benefits of each particular set. This is consistent with the cost-benefit model of choice proposed by Reutskaja and Hogarth (2006). We further speculate that the neural correlates of decision processes in the brain also consider when the effort does not pay off. Therefore, when confronted with large sets "the brain" simply does not waste precious resources and does not put a lot of effort in choosing.

On the other hand, it is important to note that different parts of the ACC were associated with different tasks in our experiment. While activation in the dorsal part of the ACC showed an inverted U-trend, activation of the more ventral part of the ACC was correlated with the subjective difficulty ratings in our task.

SPL activation was associated with the subjective perception of choice set value in our experiment. Apart from that, we found that SPL activation was modulated by the number of items in the set, number of saccades, and choice "freedom". First, SPL activation was higher in free as opposed to forced choice trials. There may be two possible explanations for the distinction in SPL activity in NF and FO sets: different number of saccades and degree of choice "freedom". The SPL was previously shown to be involved in saccadic eye-movement planning and execution (Andersen & Buneo, 2002; Medendorp et al., 2008). As people make more eye-movements in free than in forced choice condition, higher SPL activity is expected in the former than in the later condition. However, it is highly unlikely that saccadic eye-movements explain the difference in SPL activity in this contrast. The data show, that SPL activity in these regions is not correlated with the number of saccades, i.e. activation of the SPL in the NF > FO contrast was mapped mostly within its medial aspects, while more lateral parts of SPL were correlated with the number of saccades (Figures 3.7A; 3.7C; and 3.8). Therefore, we can rule out this explanation. On the other hand the degree of choice "freedom" may explain this difference.

Therefore, based on evidence from previous research and results from this experiment, we emphasize the role the SPL plays in the choice processes, and suggest that activity within the medial SPL is "choice-related" and plays a major role in mediating voluntary behavioral choices. It is highly likely that the activity in the SPL also reflects "how much choice is enough."

Our data suggest that the sub-regions of the parietal cortex might have different specializations: while the medial part of the SPL might play a significant role in mediating "choice" processes the more lateral SPL might be more related to eye movements planning.

Finally, our data can help understand whether "hot" or "cold" systems are involved in decision-making in choice overload situations. Behavioral research suggests that choice behavior and experience is a result of costs and benefits underlying choice (Loewenstein, 1999; Reutskaja & Hogarth, 2006). Costs associated with choice overload can be both "psychic" and "cognitive". While "psychic" costs are more emotional in nature (e.g., stress and discomfort), "cognitive" costs (e.g., difficulty to make rational trade-offs) belong more to the "cold" system of the human being. Interestingly, most of the task-related areas in our experiment were in good special correspondence with regions that have been associated with "cognitive" rather than "emotional" processes in previous research. Moreover, there was no significant activity found in the amygdala or insula, i.e. areas that were highly associated with emotional experiences during decision-making tasks in previous research (e.g, Paulus et al., 2003; De Martino et al., 2006). Activity in such "analytic" areas as the MFG, dACC or SPL, however, was modulated by the number of items in the set and by subjective experiences of the participants. It is worth mentioning, that some areas that showed significant activation in our tasks are thought to be correlated with "positive" rather than "negative" emotional states (such as "reward" in the NA, Caudate, or POG)[24]. Therefore, our results suggest that while positive sides of choice might be experienced with both the "heart" and "mind", the costs of choice might be more cognitive (i.e., based on calculations and physical requirements) than emotional in nature.

In this paper we presented the first experiment which aimed to explore the neural correlates of the choice overload phenomena. The results of our experiment showed that brain activity was modulated by the number of choices available to the participants, by subjective perceptions about the choices and choice experience, by availability of a clear favorite item as well as by the "freedom of choice". Though there is still a long journey to the final destination of understanding of "how much choice is enough", we believe that the data presented shed light on the mechanisms underlying choice from sets with multiple alternatives, and inform predictions of human decision making in choice overload situations.

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[24] We also found the ventral ACC to be modulated by difficulty ratings. As this area is known as "emotional" ACC (Bush et al., 2000; Rogers, et al 2004), it is likely that some costs may be emotional in nature. However, no other areas known for processing negative emotions were associated with costs of choosing..

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Appendix 3.A: Equipment and acquisition of biological Data

Eye- and finger-tracking analysis. Eye-movements of participants were recorded by the ViewPoint Eye Tracker (Arrington Research Inc., Scottsdale, USA) and registered by fMRI-compatible eye-camera (Resonance Technology Inc., USA) while participants were performing the task in the fMRI scanner. Eye-movements were recorded at 60HZ frequency. Saccades were detected using an absolute velocity threshold (>20deg/sec).

Finger responses were recorded using an MRI-compatible diamond-shaped four button response-box (Current Designs, Philadelphia) which was placed at a comfortable position near the subject's belly. Subjects could move the cursor (i.e. the green frame) up, down, left or right by pressing the corresponding buttons. Subjects could not make diagonal movements. Reaction time was defined by the amount of time that elapsed until subjects started to move the cursor towards the item of their choice since the appearance of the response screen.Eye-movements and finger responses were analyzed using Matlab7.1.

Image acquisition and fMRI analysis. A 3-tesla Siemens TRIO scanner and an 8-channel head coil (Siemens, Erlangen, Germany) were used to acquire MRI-images. T1-weighted MP-rage anatomical scan (176 slices, slice thickness=1mm, gap=0mm, in-plane voxel size=1x1mm, TR=1500ms, TE=3.05ms, FOV=256x256, resolution = 256x256) as well as T2*-weighted gradient-echo planar imaging scans (EPIs: slice thickness=3.5mm, gap=0mm, in-plane voxel size=3x3mm, TR=2000ms, TE=30ms, flip angle=90°, FOV=192x192, resolution=64x64, 32 axial slices) were obtained for each subject, providing an almost entire coverage of the cerebral cortex as well as most sub-cortical structures (for several subjects only the posterior parts of cerebellum were not covered, and there were also dropouts in the frontal part of the brain for several participants). In total, 1512 EPIs per subject were collected during three consecutive runs lasting about 13 min each.

We used SPM 5 (Wellcome Department of Cognitive Neurology, London) to perform functional image analysis. First, images of each subject were realigned to the first scan. We co-registered T1 anatomical images the mean image of the functional scans and then aligned to the SPM T1-template in MNI space (Montreal Neurological Institute, mean brain). For spatial normalization we applied the resulting non-linear 3D-transformation to all images. Finally we performed spatial smoothing of the functional images with a Gaussian filter (7x7x7 mm^3 full-width at half-maximum) and high pass filtering (cut-off period 128 ms). We did not perform slice-time correction since scans were acquired in an interleaved fashion.

Appendix 3.B: Descriptive statistics of liking ratings

Ratings of the landscape images

The liking ratings of the landscape images given by19 subjects followed normal distribution (M=4.45, SD=2.18). Subjects took on average 2835 ms to rate each image in the first round of ratings. That was on average 594 ms longer than the mean time spent per image in the second round (t=8.21, p=0.000). The data also shows that time spent per image increased significantly with the liking rating of the image, i.e. with every point increase in the liking rating subjects spent 94ms longer on evaluating the image (t=2.71, p=0.014; analysis is performed by regressing time spent on evaluating the image on liking rating assigned to the image, controlling for individual differences by including dummies for each subjects).

The liking ratings showed significant correlation between rounds 1 and 2, suggesting that subjects had similar preferences for the same picture and rated the same image similarly in both rounds. Moreover, liking ratings did not differ significantly in the first and second round (t= 1.65, p= 0.116; analysis is performed by regressing liking rating on round dummy, controlling for individual differences by including dummies for each subject).The liking ratings also decreased as the trial time progressed. However, the absolute amount of the decrease in rating with the progress of the rating task is almost negligible (decrease of 0.001; t=2.00, p= 0.061; analysis is performed by regressing liking rating on order of rating, controlling for individual differences by including dummies for each subject).

Appendix 3.C: ROI analysis

ROI analysis, coordinates of the brain regions, and correlations of the extracted beta values with: subjective set value, difficulty, number of saccades, the linear and quadratic term for the number of items.

A ROI definition: # squared								
Structure	x,y,z	T-value	p	r-value				
	{mm MNI}		(uncorr.)	set value	difficulty	# sacc.	# linear	# squared
Basal Ganglia								
N Acc r	12 6 -3	4.50	0.000	-0.07	0.05	0.02	-0.08	**0.31******
Caudate r	15 18 0	4.12	0.000	-0.10	0.18	-0.13	-0.03	**0.28****
Caudate l	-12 18 0	4.08	0.000	-0.11	0.11	-0.18	-0.16	**0.33******
Cingulate Cortex								
ACC r BA 32	9 27 36	4.22	0.000	-0.05	0.14	**0.22***	0.10	**0.24***
Prefrontal Cortex								
MFG r BA 45	48 36 18	3.45	0.001	0.06	0.05	0.13	-0.07	**0.28****
MFG l BA 46	-39 51 18	3.32	0.002	-0.05	0.06	-0.10	-0.14	**0.22***
MFG l BA 44	-42 24 33	3.24	0.002	0.07	-0.13	-0.02	-0.02	**0.28****
MFG l BA 46	-33 36 33	3.15	0.003	0.00	-0.04	-0.16	-0.13	**0.26****
Orbitofrontal Cortex								
POG l BA 47	-30 27 -9	3.33	0.002	-0.07	-0.03	0.15	-0.04	**0.31******
POG l BA 47	-27 36 -12	3.31	0.002	0.06	0.02	-0.04	**-0.25****	**0.3****
Premotor Cortex								
PMv r BA 6	63 3 30	3.11	0.003	-0.06	0.12	**-0.24***	-0.10	**0.19***
PMv r BA 6	48 9 21	3.10	0.003	0.12	-0.03	0.02	-0.08	**0.26****
Parietal Cortex								
POTZ r	21 -78 36	2.96	0.004	-0.07	**-0.19***	0.06	-0.07	**0.23***
SPL r BA 7	18 -81 45	2.81	0.006	-0.05	-0.06	0.20*	-0.12	**0.21***

B ROI definition: # linear								
Structure	x,y,z	T-value	p	r-value				
	{mm MNI}		(uncorr.)	set value	difficulty	# sacc.	# linear	# squared
Occipital Cortex								
LG l BA 18	-15 -84 -9	4.10	0.000	-0.07	0.17	0.10	**0.38******	-0.07
LG l BA 18	-15 -69 -12	3.96	0.000	0.02	-0.05	0.00	**0.32******	-0.08
IOG l BA 19	-36 -75 -9	3.69	0.001	0.03	-0.07	0.08	**0.40******	-0.09
MOG l BA 19	-30 -87 21	3.97	0.000	0.05	-0.18	**0.33******	**0.37******	-0.12
MOG l BA 19	-30 -96 15	3.80	0.001	-0.09	0.09	**0.27****	**0.26****	-0.16
Parietal Cortex								
SPL l BA 7	-24 -51 45	3.64	0.001	0.01	**-0.24****	-0.08	**0.27****	0.01
Premotor Cortex								
PMd l BA 6	-24 -6 48	3.74	0.001	0.07	-0.11	0.43	**0.32******	-0.05
PMd r BA 6	33 -6 48	3.00	0.004	0.09	0.05	0.08	**0.22***	0.02
SMA r	9 9 51	3.19	0.003	-0.14	0.12	0.17	**0.29****	0.01
SMA l	-3 12 48	2.89	0.005	-0.11	**0.24****	**0.25****	**0.21***	0.08

C ROI definition: set value								
Structure	x,y,z	T-value	p	r-value				
	{mm MNI}		(uncorr.)	set value	difficulty	# sacc.	# linear	# squared
Parietal Cortex								
SPL r	12 -57 72	2.86	0.003	**0.25****	**-0.22***	0.14	-0.04	0.06
SPL r	18 -60 66	2.79	0.003	**0.26****	**-0.36******	0.15	0.03	0.03
SPL r	9 -63 63	2.59	0.005	**0.20***	-0.17	-0.16	-0.05	0.14